# Toward seasonal forecast for MARS

Objective: Exploring how to best exploit existing seasonal forecasts for crop management decision

- Review of current methodologies
- Evaluation of the forecast quality of the seasonal (re)forecasts
- Forecast for 2016 using April start date
- Alternative approaches to produce seasonal forecasts

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# Literature review: skill

Seasonal predictability of weather events is spatially as well as seasonally highly variable

The skill is high over the tropics while over the extra-tropics it is very limited

Poor forecast skill is currently observed over Europe, especially regarding the seasonal rainfall forecasts

# Literature review: next steps

Two strategies have been identified to integrate seasonal forecast in the current operational MCFYS:

1. Implementation of a test environment based on a suite of climatic indicators at global scale

2. Exploration of new approaches to achieve crop yield estimation for Europe based on seasonal forecasts by evaluating the potential for an empirical model to achieve crop yield estimation based on seasonal forecasts

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- Evaluation of the forecast quality of the seasonal (re)forecasts
  - Monthly averages
  - Daily indices

# Preliminary results: Skill of seasonal temperature forecasts

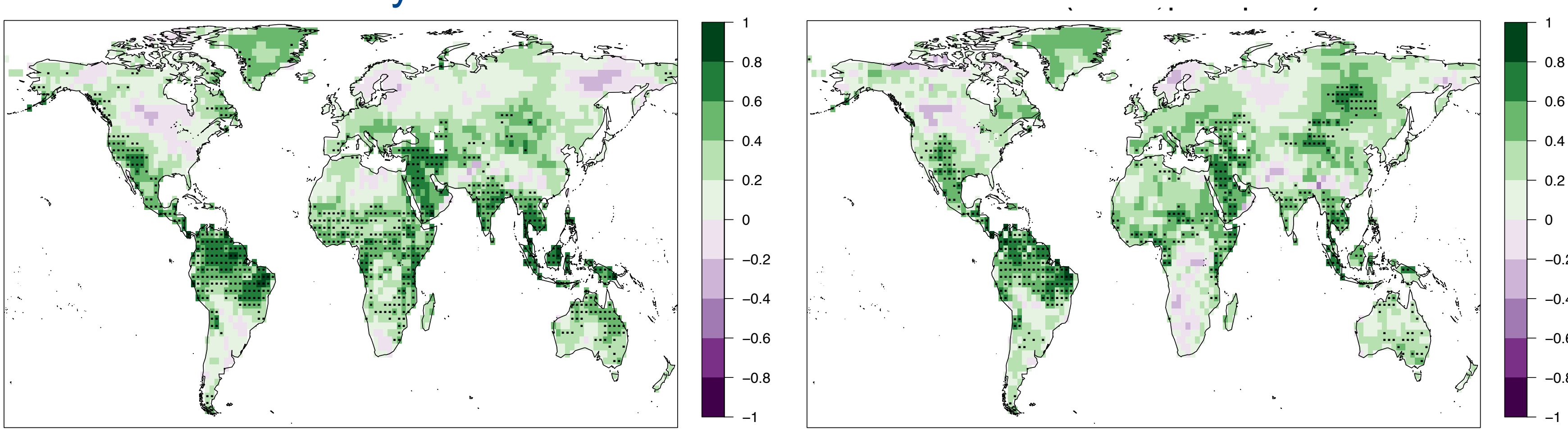


## Correlation of temperature forecasts wrt ERA-Interim over 1982-2014

June (May init.)

ECMWF-System 4

CFSv2

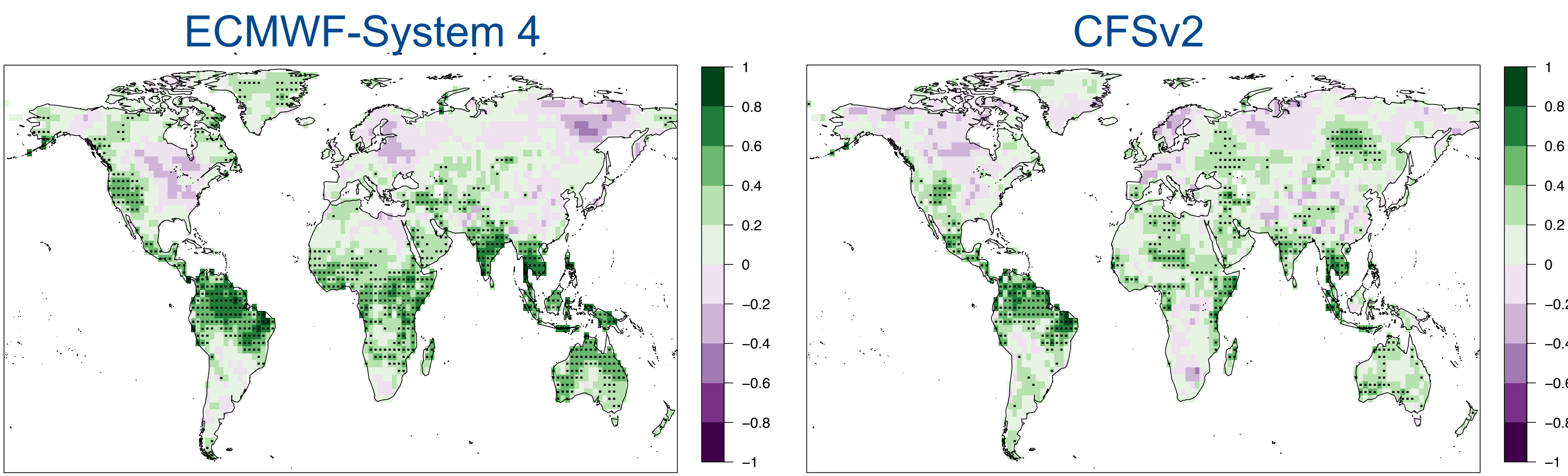



- High forecast skill over tropical regions
- ECMWF-System4 generally (also looking other other start dates/lead times) better than CFSv2

# Preliminary results:
# Skill of seasonal temperature forecasts

## Correlation of temperature forecasts
## wrt ERA-Interim over 1982-2014. **Detrended Data**

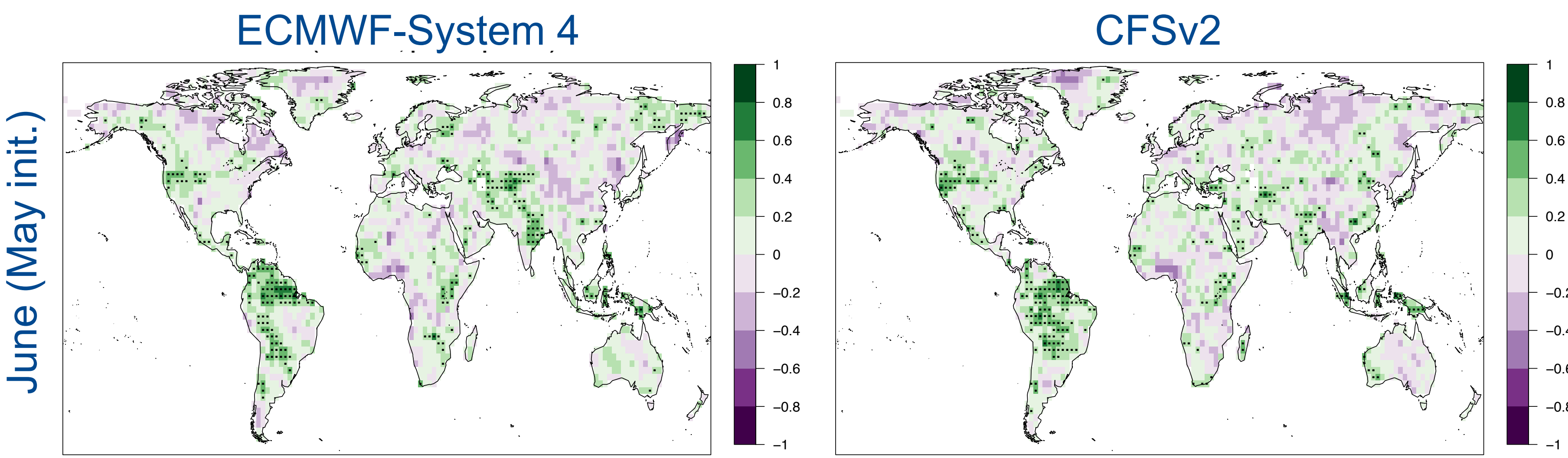
June (May init.)




Climate change is an important source of predictability, manly in mid-latitudes

# Preliminary results:
# Skill of seasonal precipitation forecasts

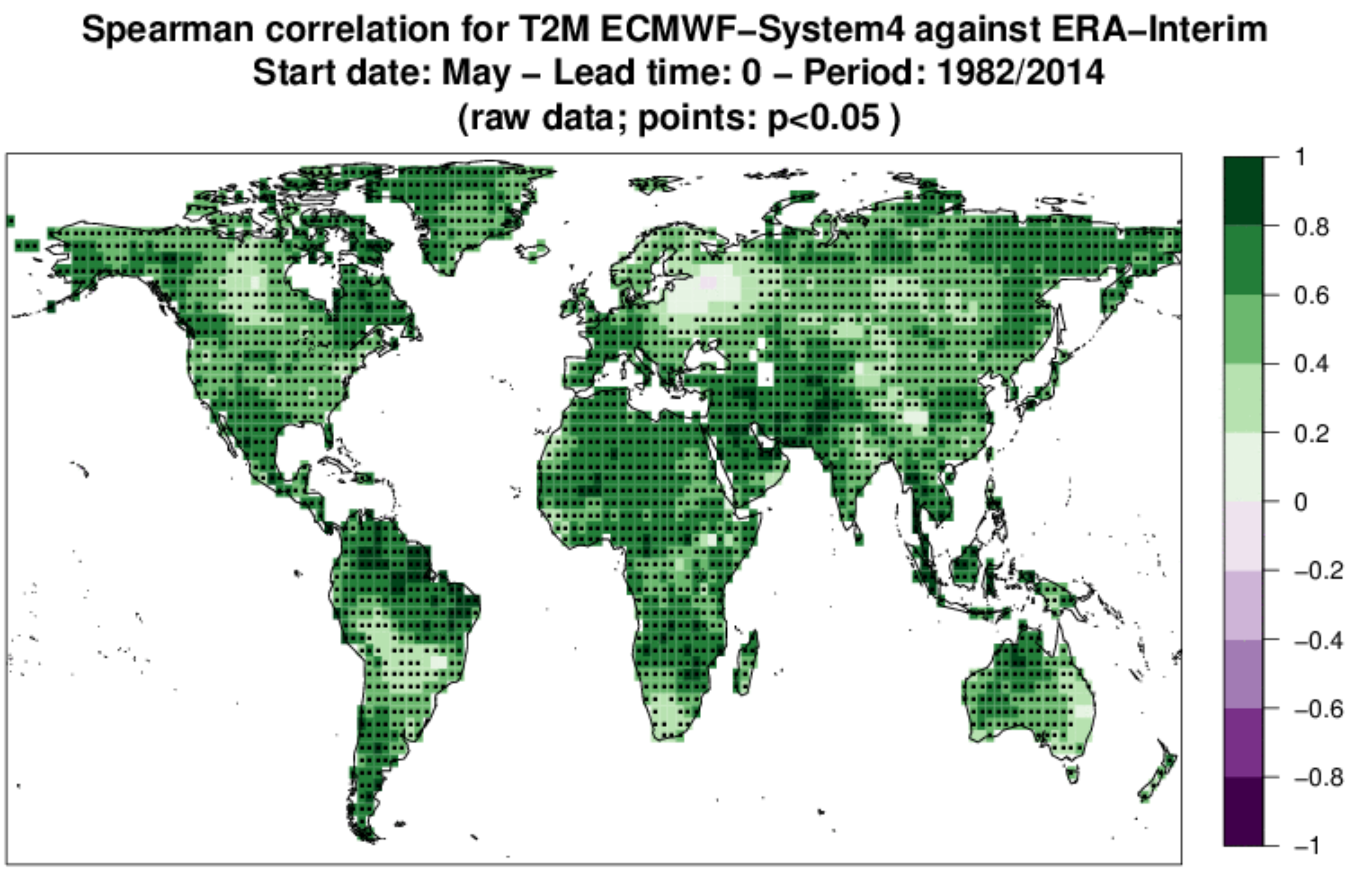
## Correlation of temperature forecasts wrt ERA-Interim over 1982-2014




- Precipitation forecast skill lower than that of temperature
- ECMWF System4 and CFSv2 in general perform similarly

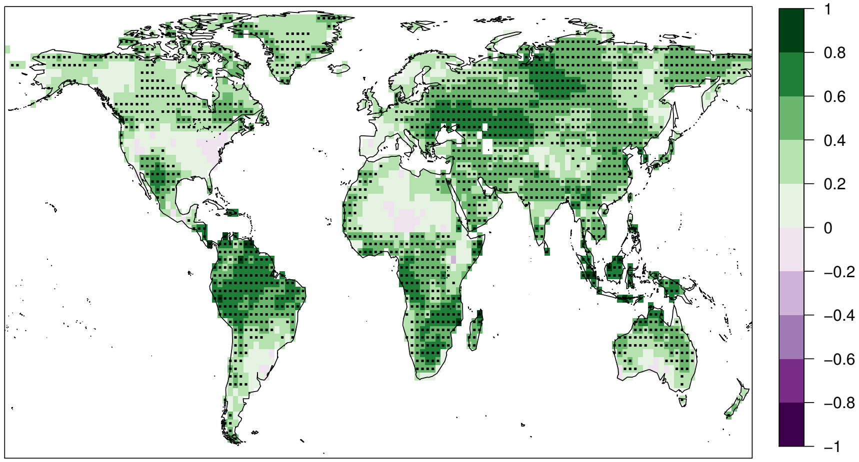
# Preliminary results: Lead time skill evolution

## Lead times: from 0 to 6 months ahead

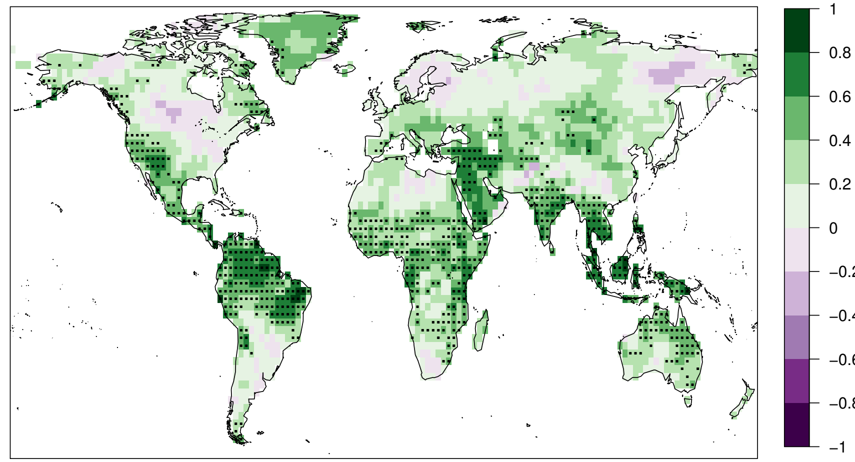


# Preliminary results: skill dependence on the seasons

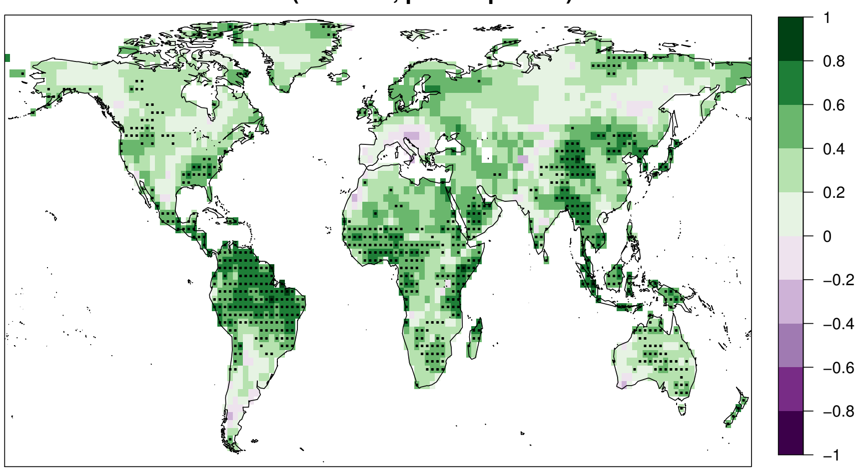
**Spearman correlation for T2M ECMWF–System4 against ERA–Interim**
**Start date: February – Lead time: 1 – Period: 1982/2014**
**(raw data; points: $p<0.05$ )**



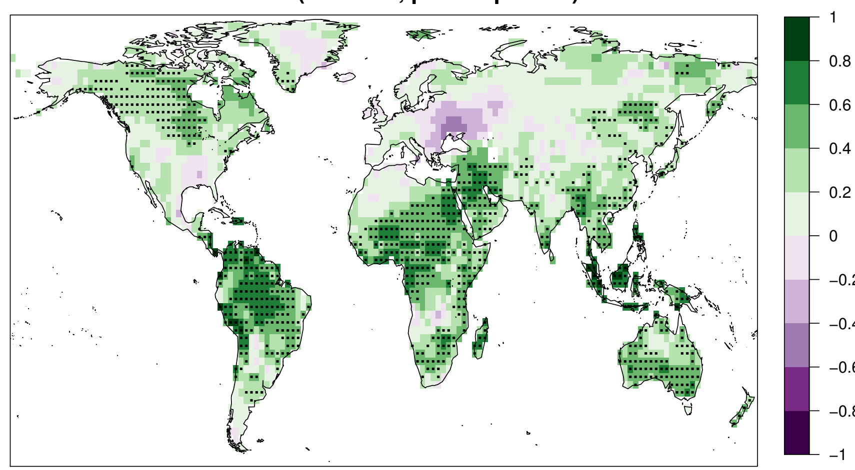

**Spearman correlation for T2M ECMWF–System4 against ERA–Interim**
**Start date: May – Lead time: 1 – Period: 1982/2014**
**(raw data; points: $p<0.05$ )**




**Spearman correlation for T2M ECMWF–System4 against ERA–Interim**
**Start date: August – Lead time: 1 – Period: 1982/2014**
**(raw data; points: $p<0.05$ )**




**Spearman correlation for T2M ECMWF–System4 against ERA–Interim**
**Start date: November – Lead time: 1 – Period: 1982/2014**
**(raw data; points: $p<0.05$ )**

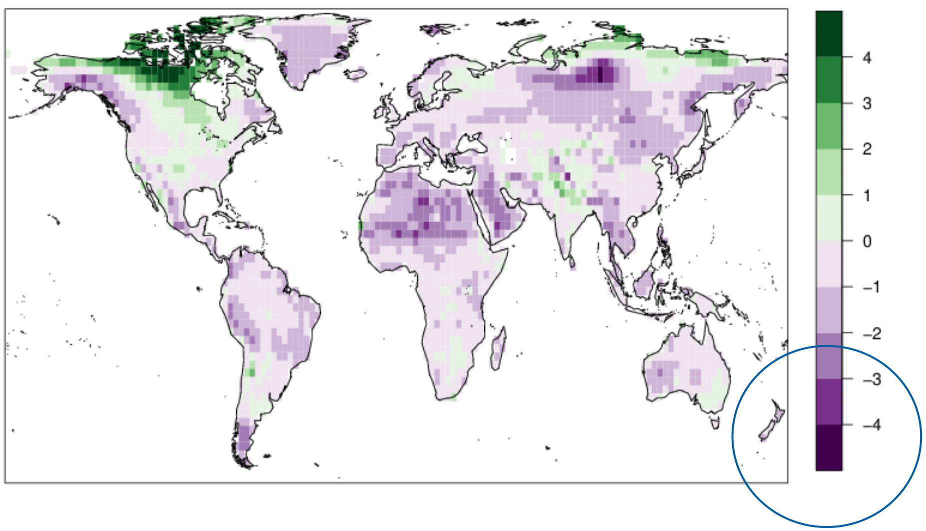


# Preliminary results: bias and drift

Bias of ECMWF-System 4 seasonal forecasts (lead times: from 0 to six month ahead) of temperature wrt ERA-Interim over 1982-2014

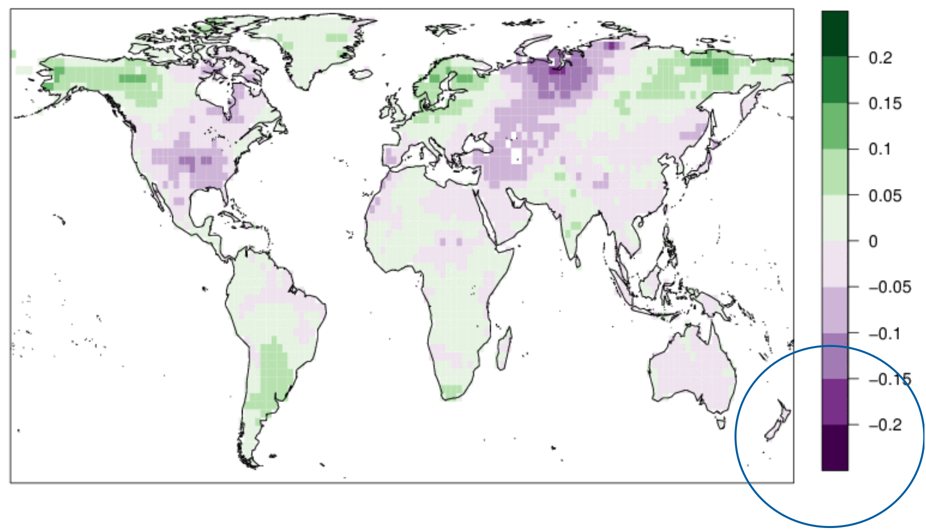
## RAW DATA

**Bias T2M ECMWF–System4 against ERA–Interim**
**Start date: May – Lead time: 0 – Period: 1982/2014**




## BIAS CORRECTED DATA

**Bias T2M S4 – BIAS CORRECTED against ERA–Interim**
**Start date: May – Lead time: 0 – Period: 1982/2014**

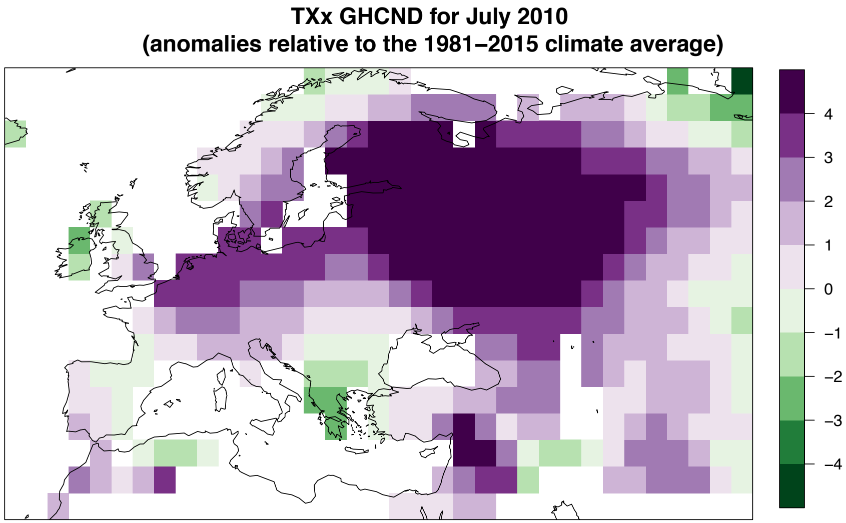


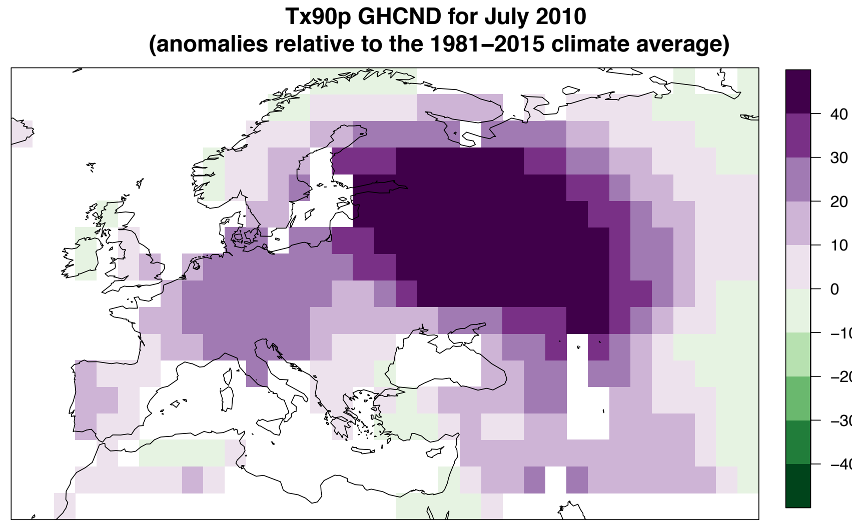

Bias correction: simple linear scaling performed in a leave-one-out cross validation mode

# Toward seasonal forecast for MARS

- Evaluation of the forecast quality of the S4 reforecasts
  - Monthly averages
  - Daily indices

# Preliminary results: 2010 heatwave

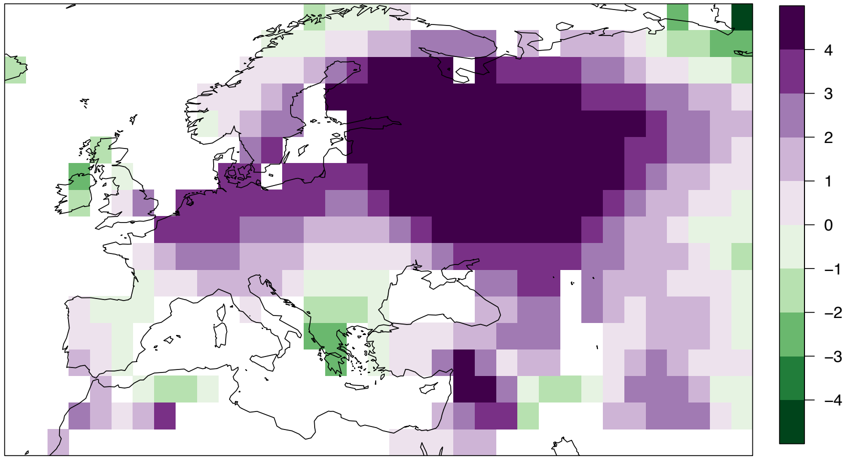


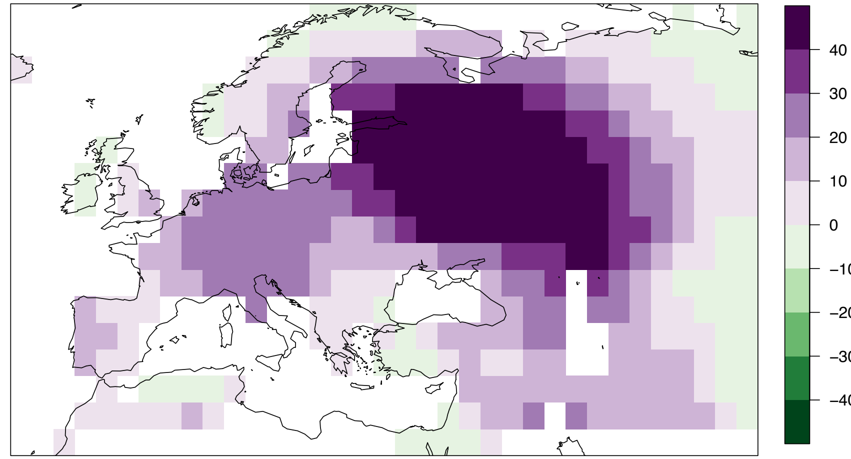
# Preliminary results: 2010 heatwave



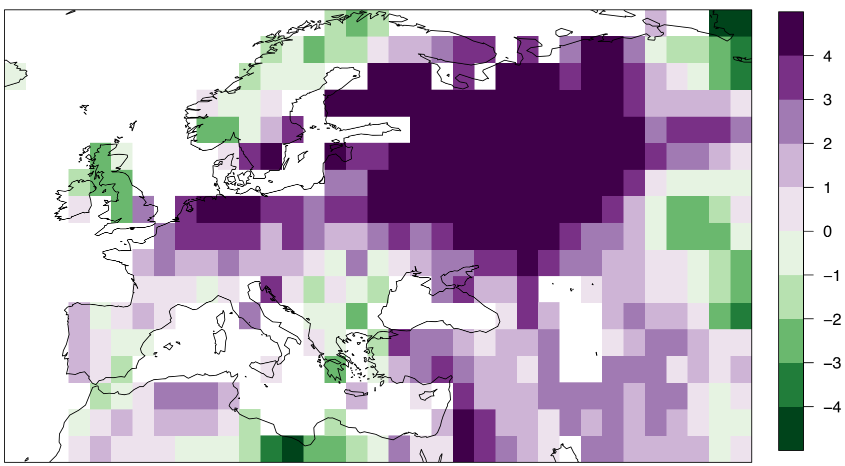
**TXx GHCND for July 2010**
**(anomalies relative to the 1981–2015 climate average)**



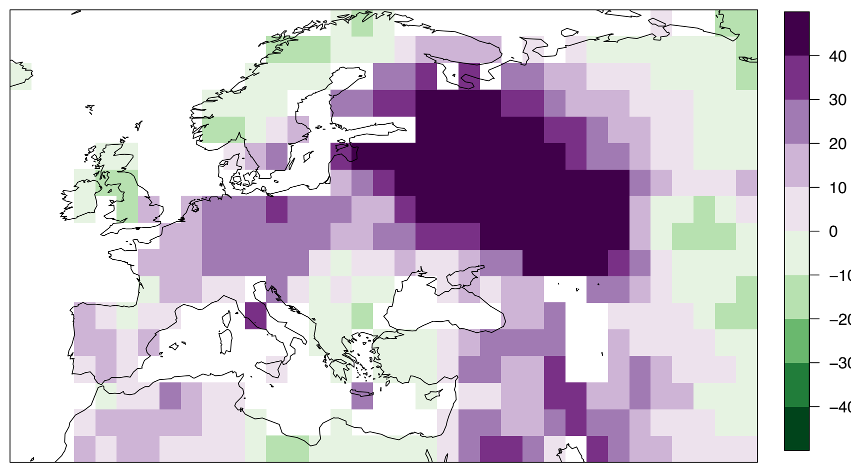

**Tx90p GHCND for July 2010**
**(anomalies relative to the 1981–2015 climate average)**




**TXx ERA–Interim for July 2010**
**(anomalies relative to the 1981–2015 climate average)**




**Tx90p ERA–Interim for July 2010**
**(anomalies relative to the 1981–2015 climate average)**



# Preliminary results: TXx assessment at global scale

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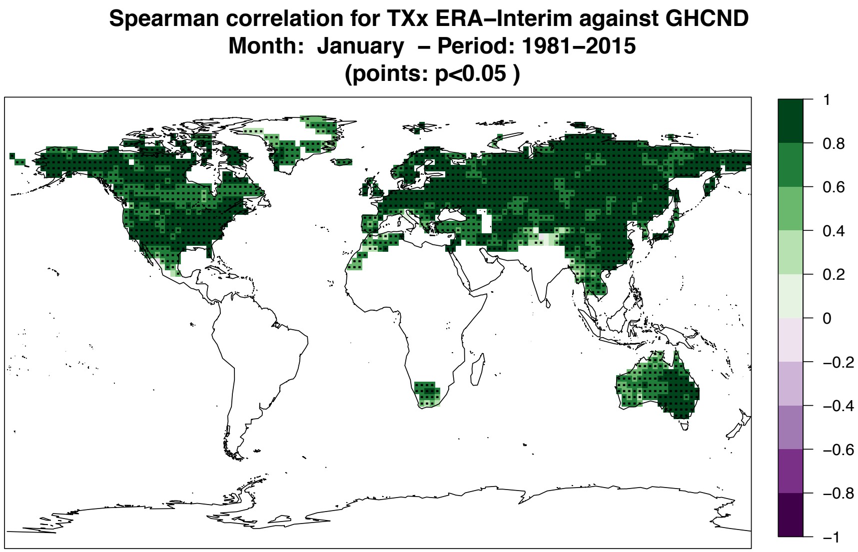
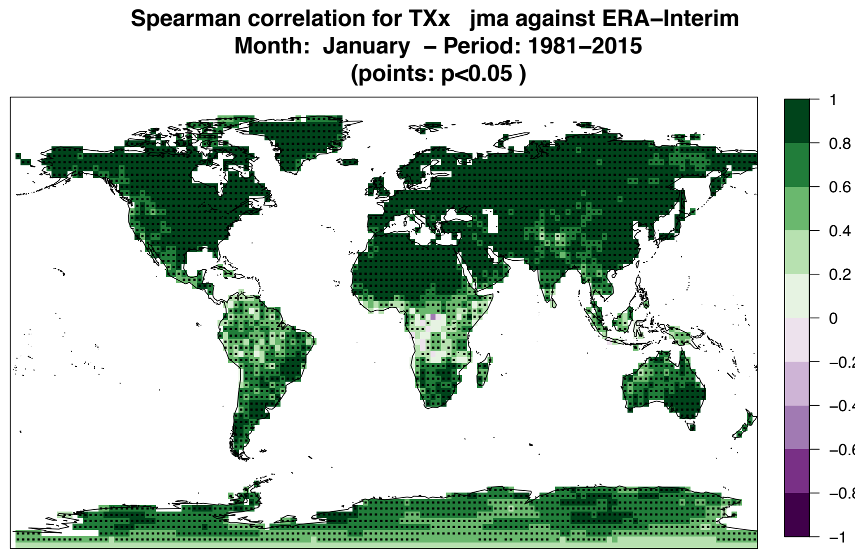
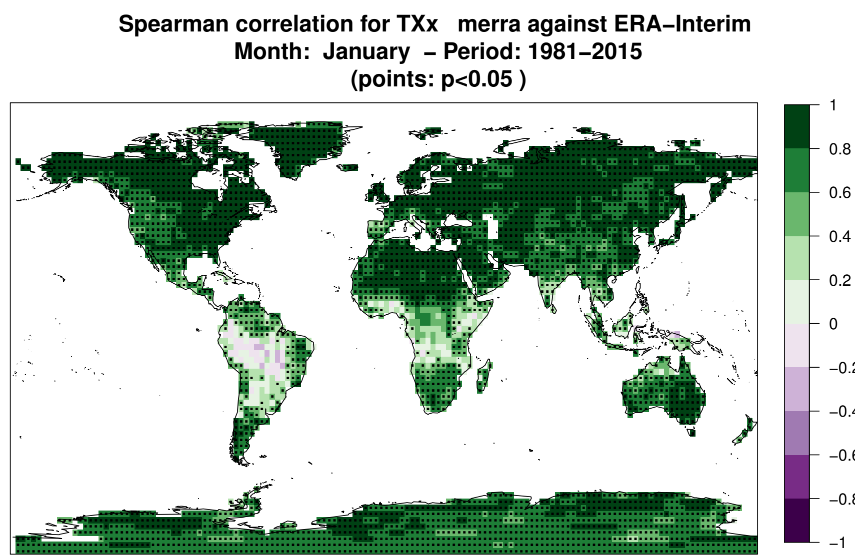


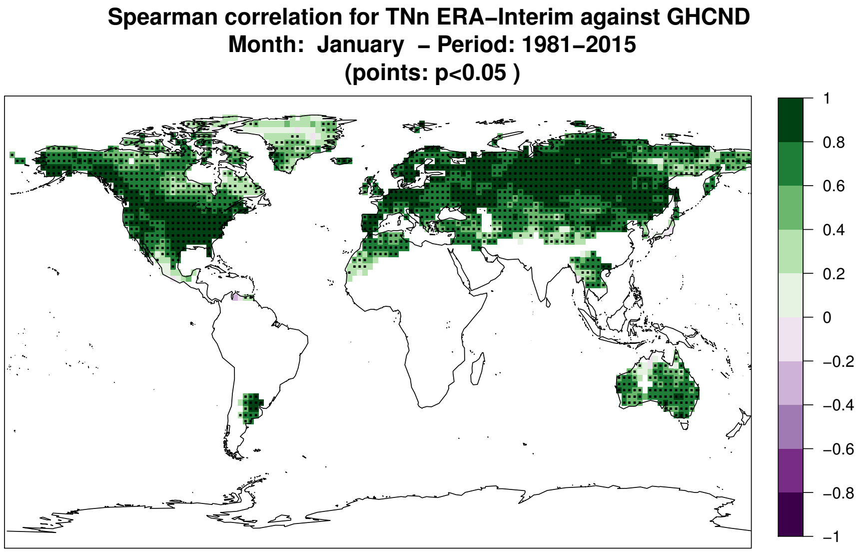



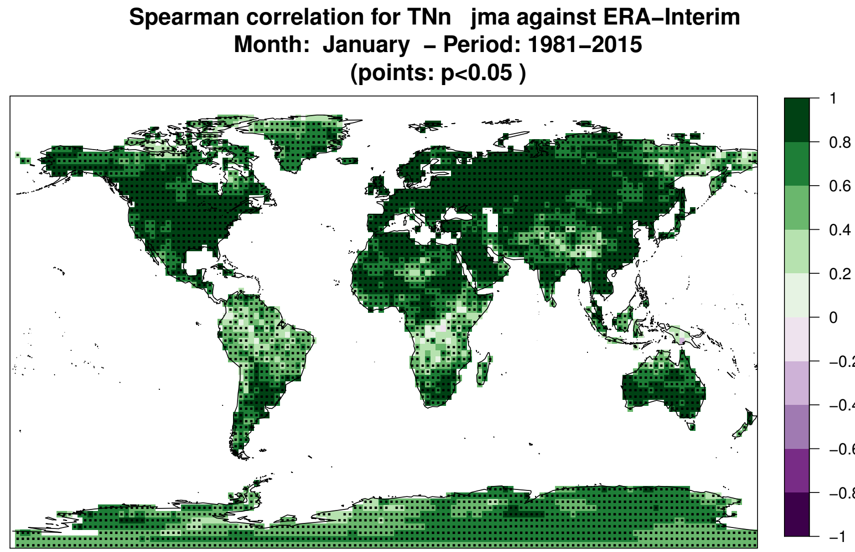



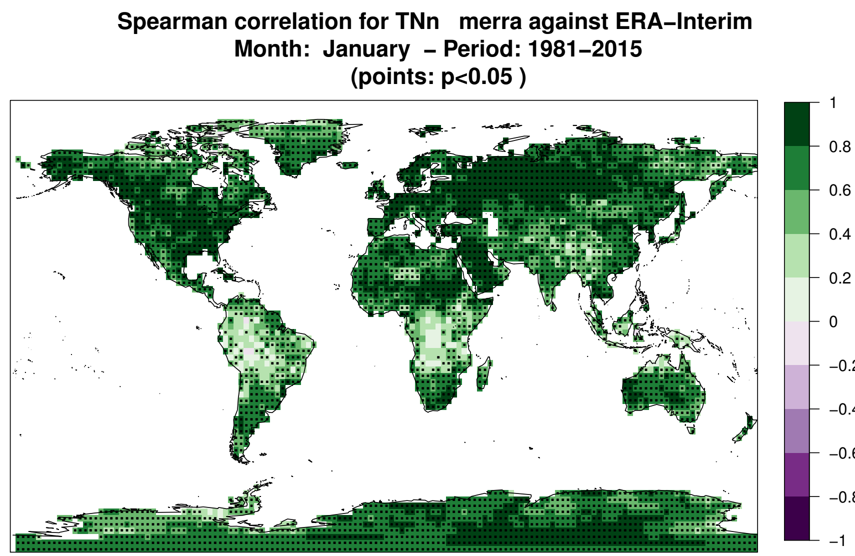

Generally high agreement among the datasets but caution is required over poor station covered regions

TXx= Monthly maximum of daily maximum temperatures

# Preliminary results: Cold extremes




Generally similar results as for hot extremes

TNn= Monthly minimum of daily minimum temperatures

# Preliminary results: Heat stress index

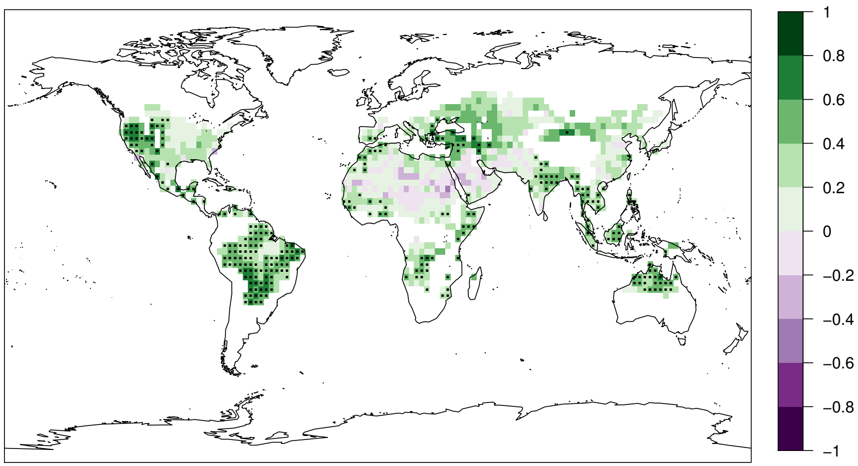


HD30 (Hot Days Index): Number of days when maximum temperature is above 30°C (masked where the observed average is < 5 days)

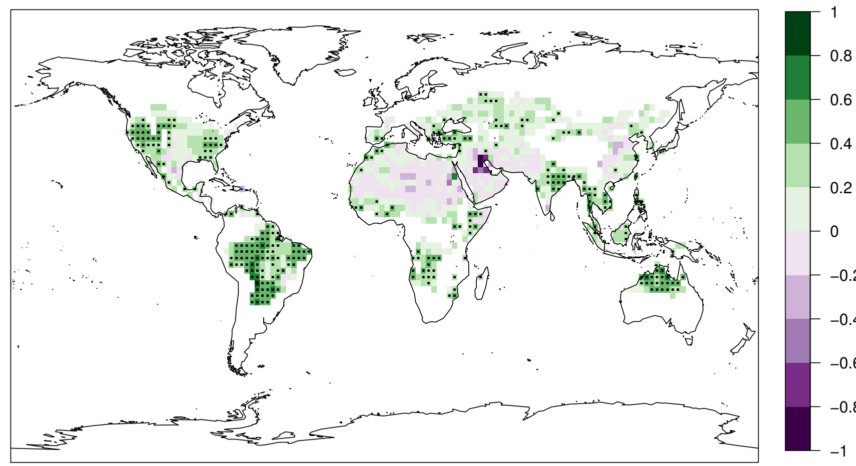
Correlation of HD30 forecasts wrt ERA-Interim over 1982-2014

June (May init.)

Raw data




Detrended data



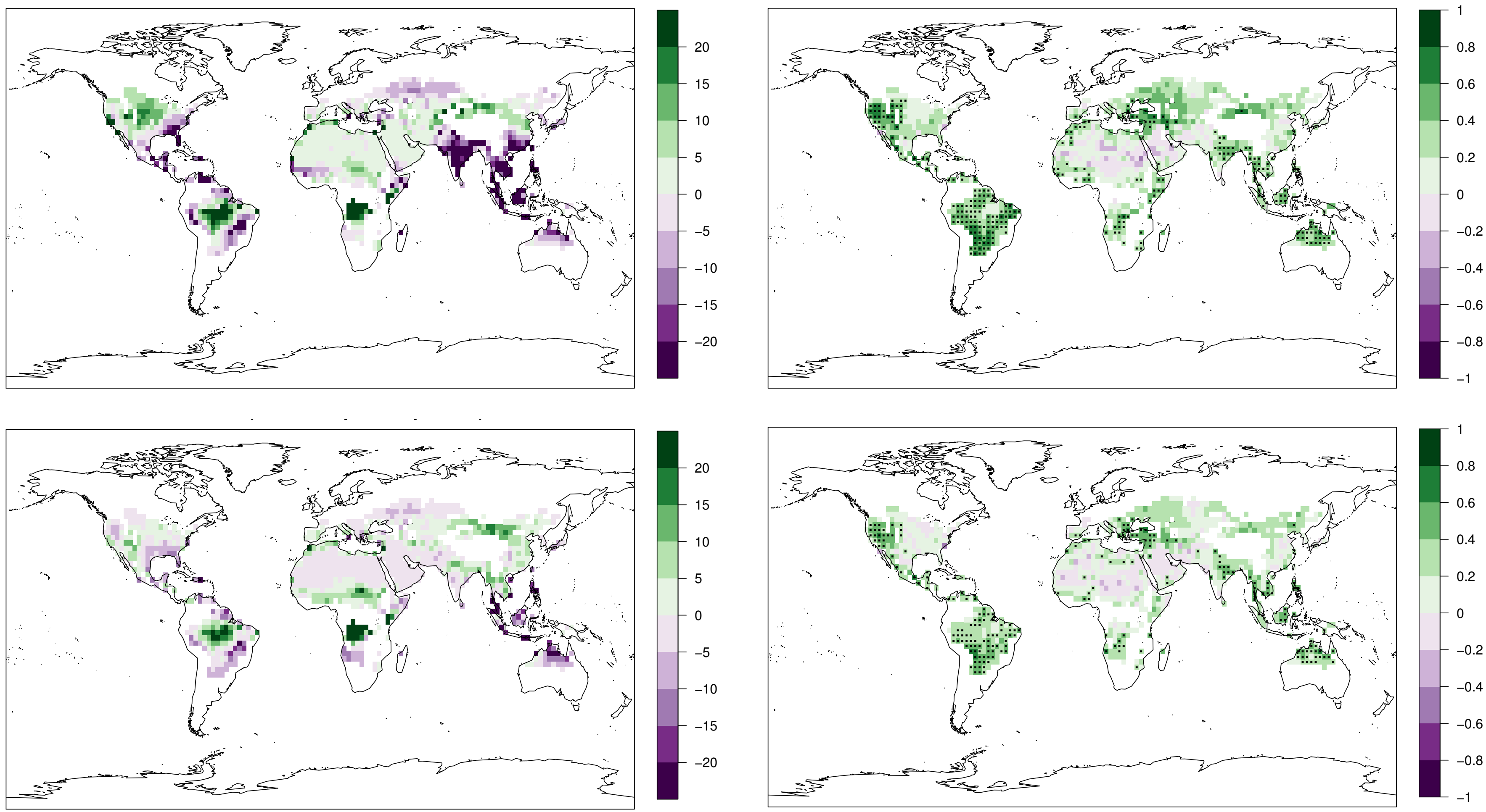
# Preliminary results: heat stress index

## Correlation of HD30 June (May init.) forecasts wrt ERA-Interim over 1982-2014

Bias | Correlation

Raw data

Bias corrected



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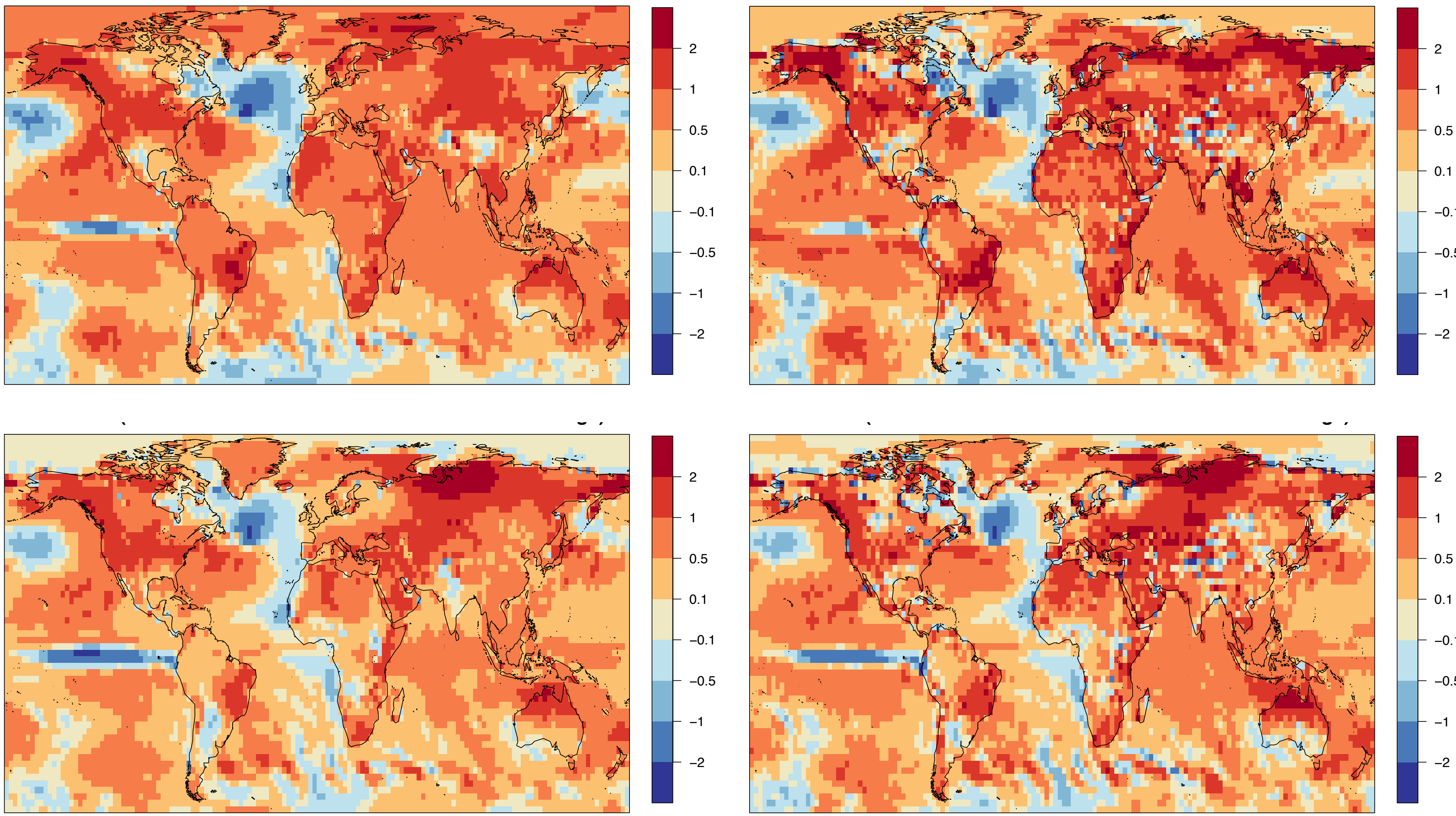
# Temperature forecasts, April 2016 init.

Mean temperature TXx

May

June



# Temperature forecasts, April 2016 init.

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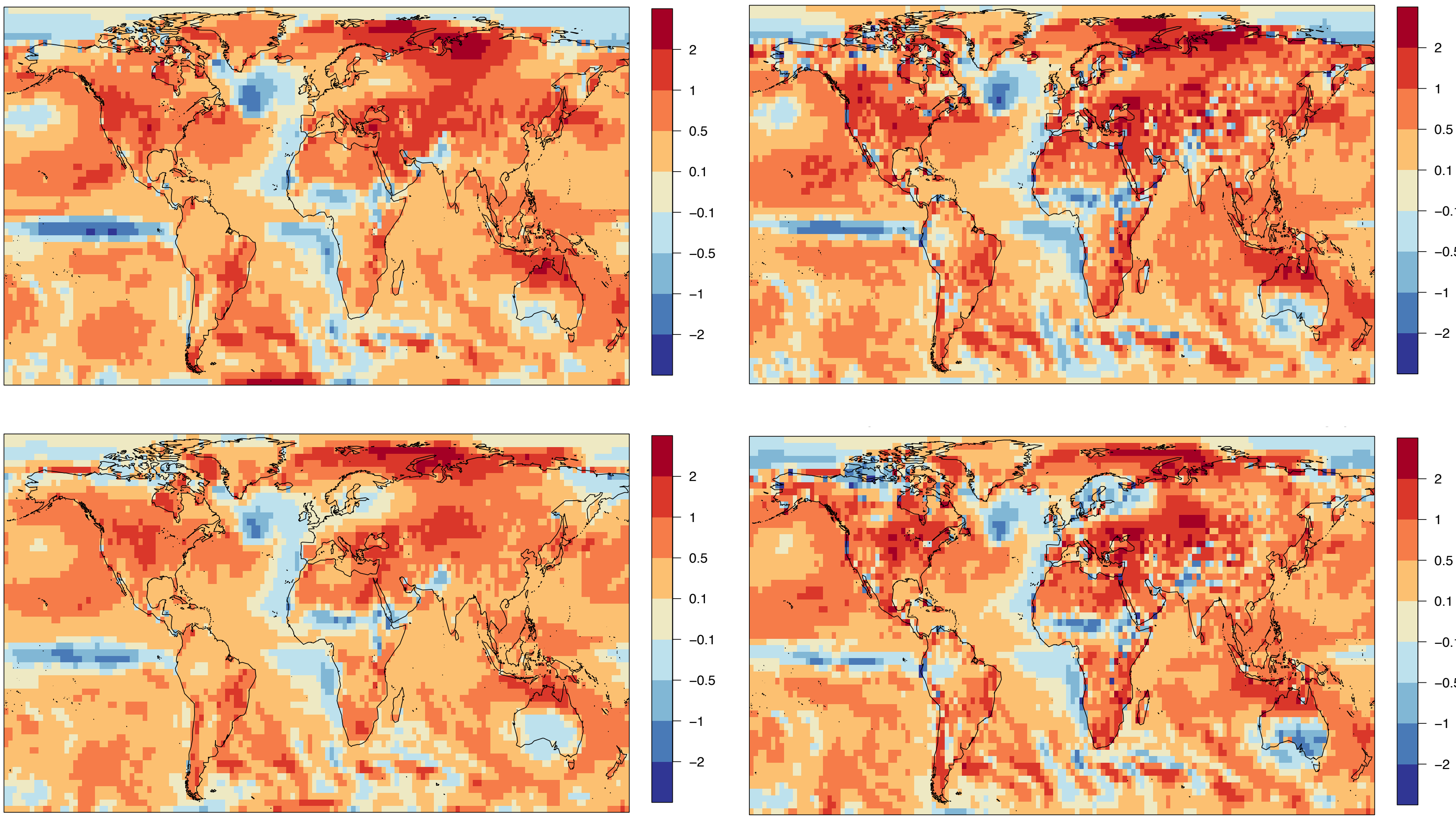
Mean temperature

TXx

July

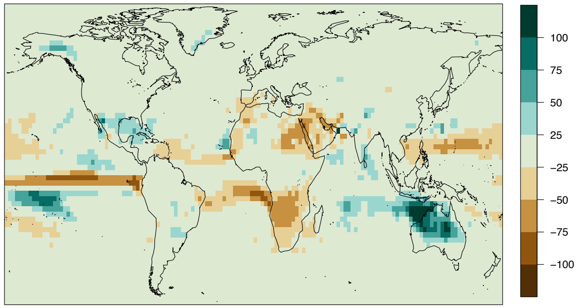
August



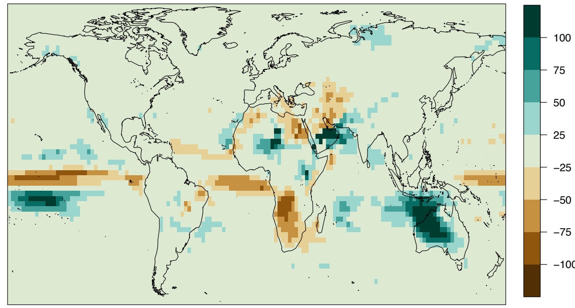
# Precipitation forecasts



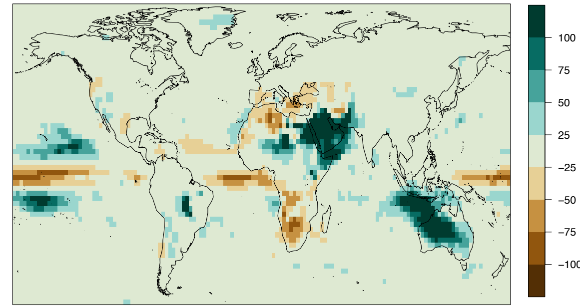
**ECMWF Seasonal Forecast: Mean precipitation anomaly (%) for May 2016**
**Forecast start date is April**
**(percentage relative to the 1981–2010 climate average)**



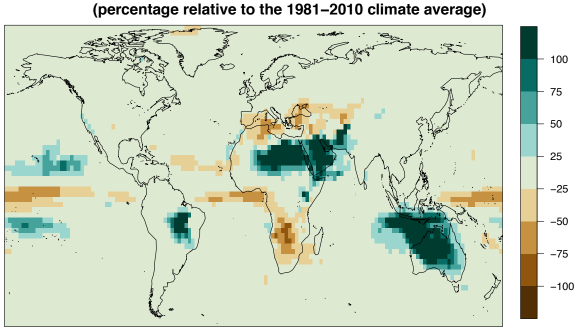

**ECMWF Seasonal Forecast: Mean precipitation anomaly (%) for June 2016**
**Forecast start date is April**
**(percentage relative to the 1981–2010 climate average)**



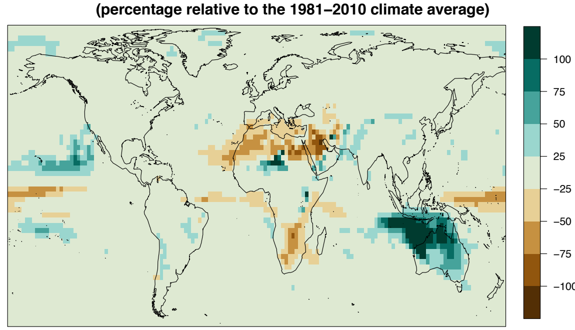

**ECMWF Seasonal Forecast: Mean precipitation anomaly (%) for July 2016**
**Forecast start date is April**
**(percentage relative to the 1981–2010 climate average)**



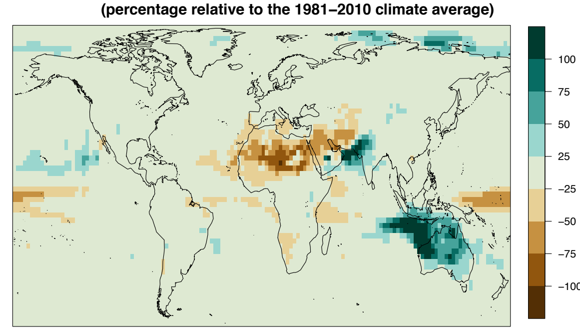

**ECMWF Seasonal Forecast: Mean precipitation anomaly (%) for August 2016**
**Forecast start date is April**
**(percentage relative to the 1981–2010 climate average)**



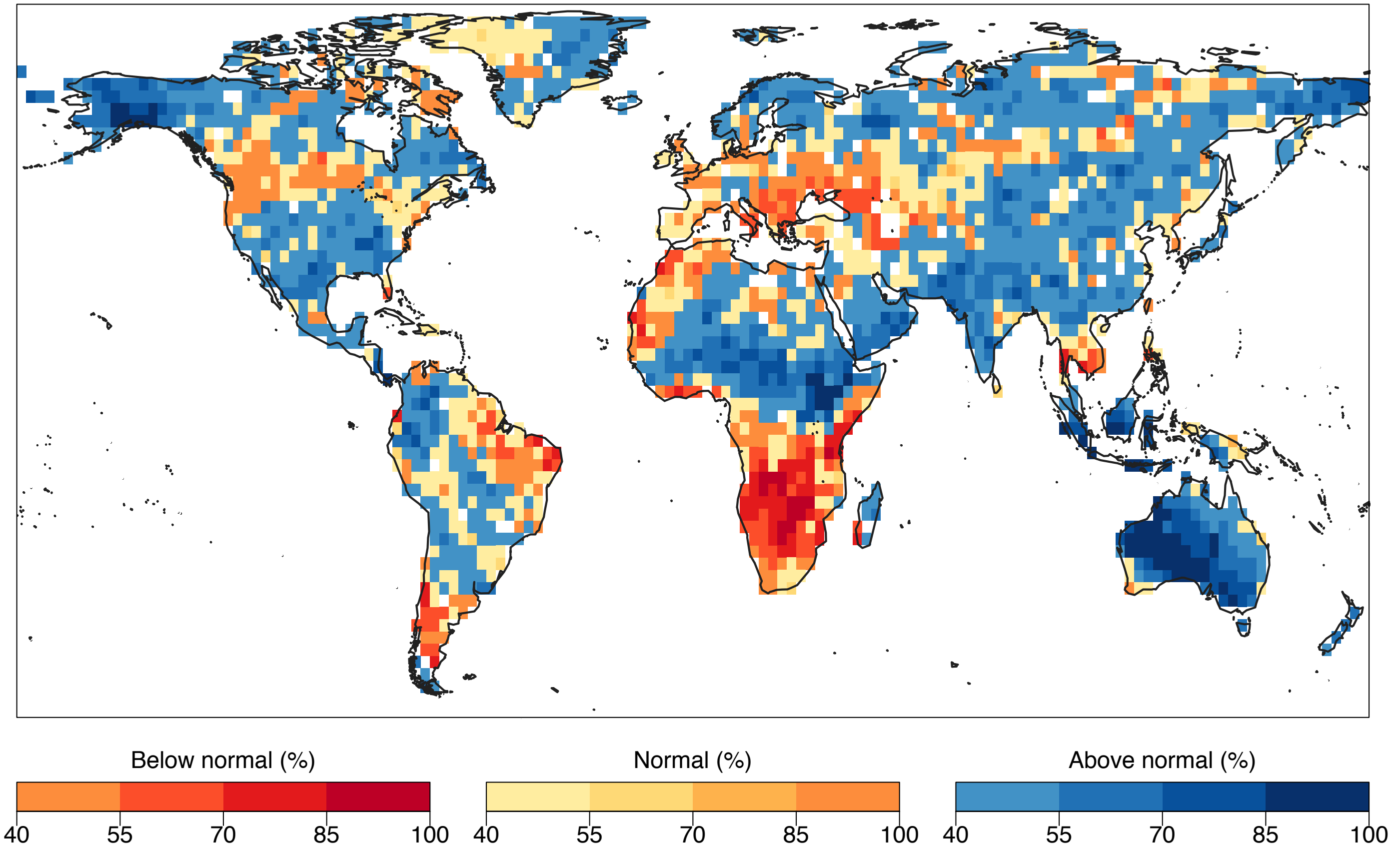

**ECMWF Seasonal Forecast: Mean precipitation anomaly (%) for September 2016**
**Forecast start date is April**
**(percentage relative to the 1981–2010 climate average)**




**ECMWF Seasonal Forecast: Mean precipitation anomaly (%) for October 2016**
**Forecast start date is April**
**(percentage relative to the 1981–2010 climate average)**

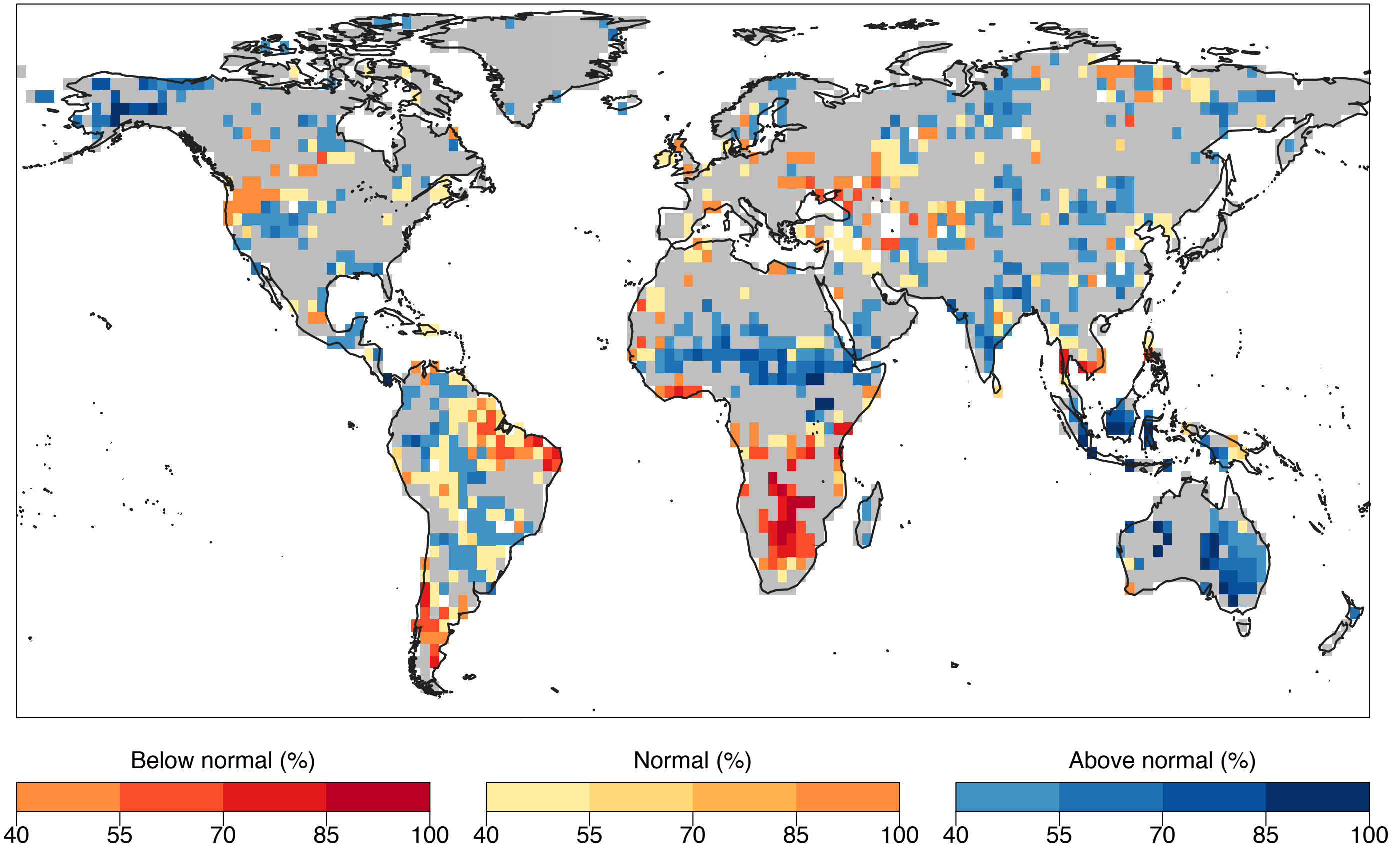


# Probabilistic forecasts: precipitation



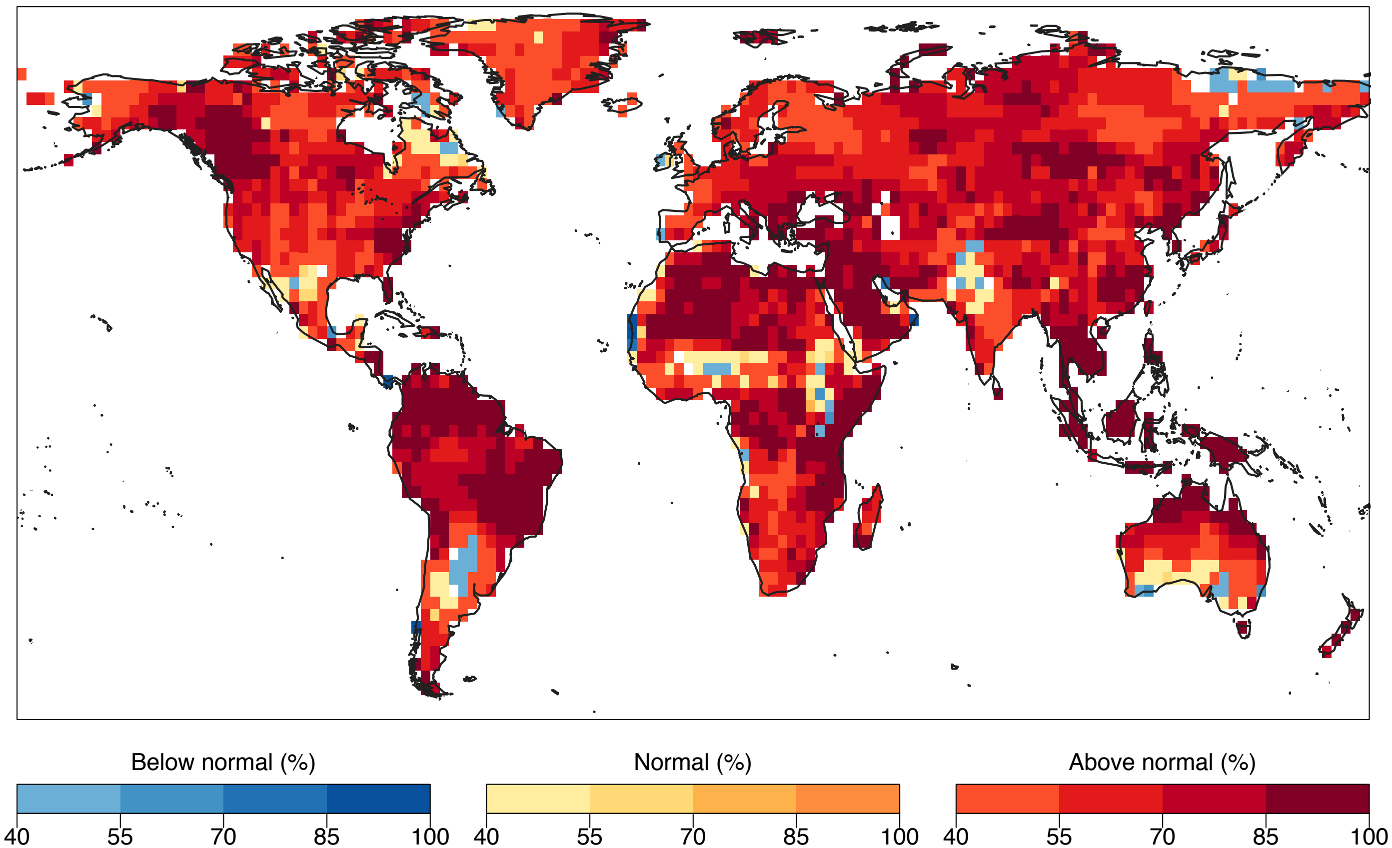

ECMWF S4 precipitation forecast for MJJA 2016 (init. April).
The most likely precipitation category (below-normal, normal or above normal) and its percentage probability to occur is shown.
White areas (over land) show where the probability is less than 40 % and approximately equal for all three categories.

# Probabilistic forecasts: precipitation



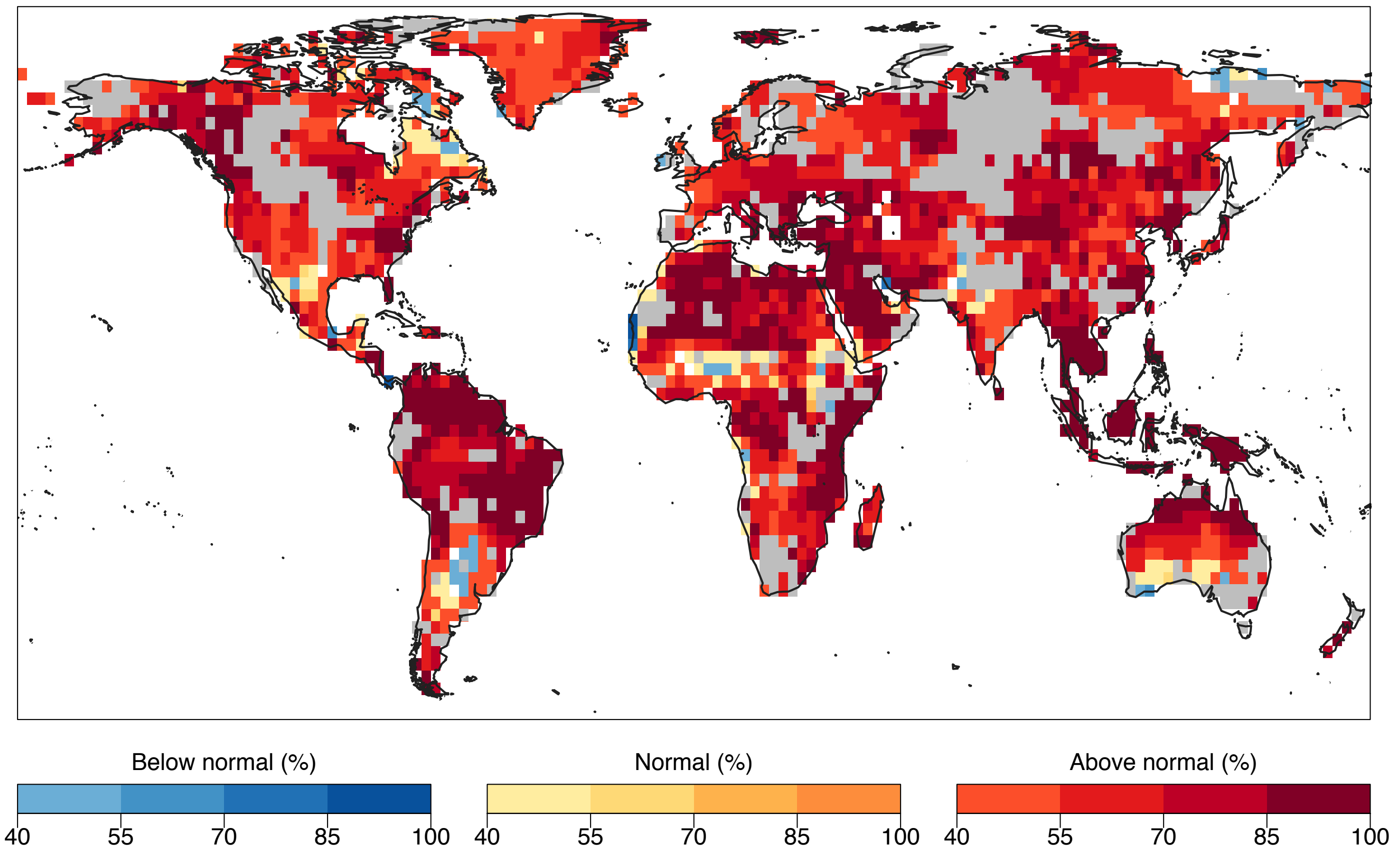

ECMWF S4 precipitation forecast for MJJA 2016 (init. April).
The most likely precipitation category (below-normal, normal or above normal) and its percentage probability to occur is shown.
**White areas** (over land) show where the probability is less than 40 % and approximately equal for all three categories.
**Grey areas** show where the climate prediction model doesn't improve the climatology.

# Probabilistic forecasts: temperature



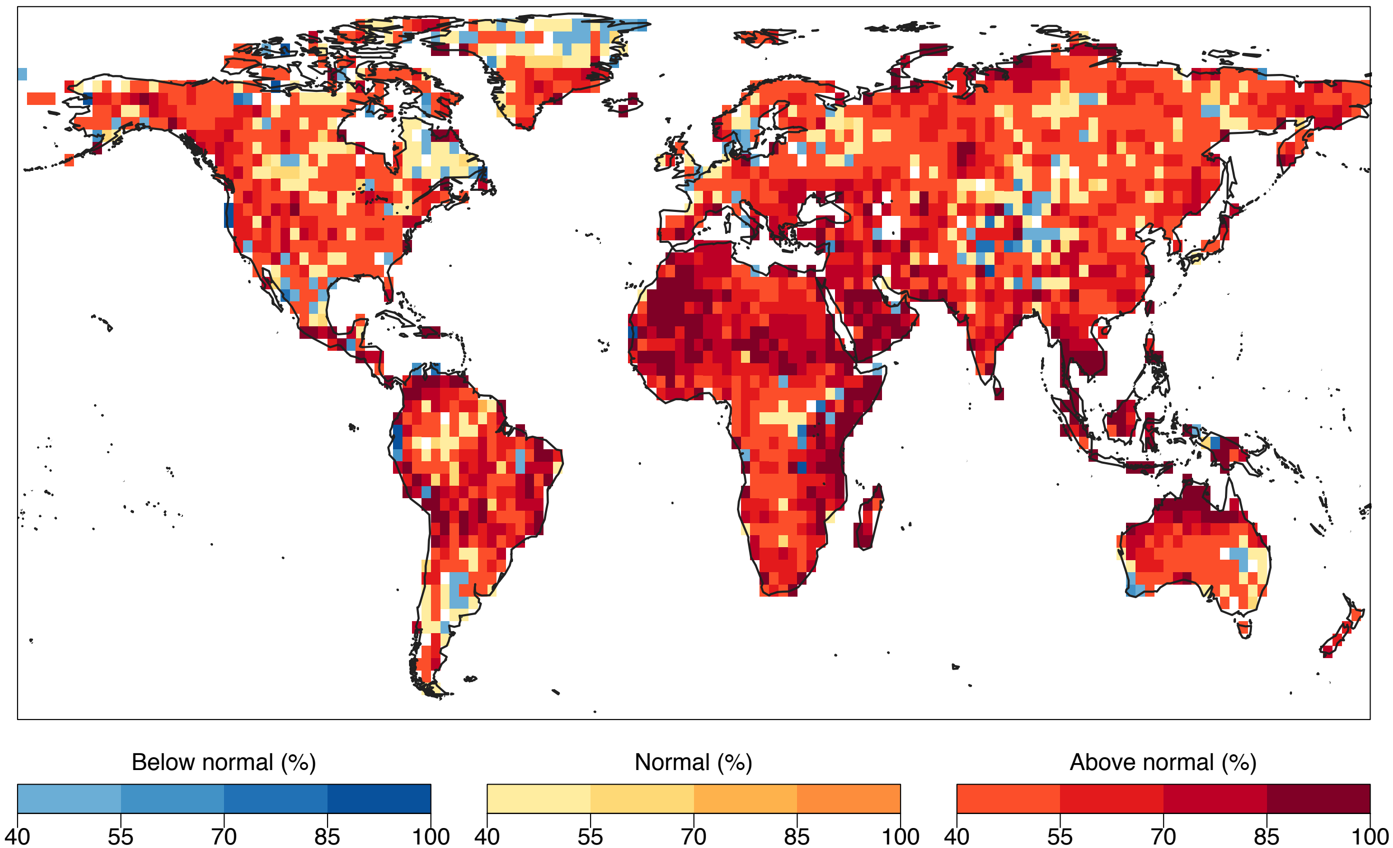

ECMWF S4 temperature forecast for MJJA 2016 (init. April).

# Probabilistic forecasts: temperature




ECMWF S4 temperature forecast for MJJA 2016 (init. April).

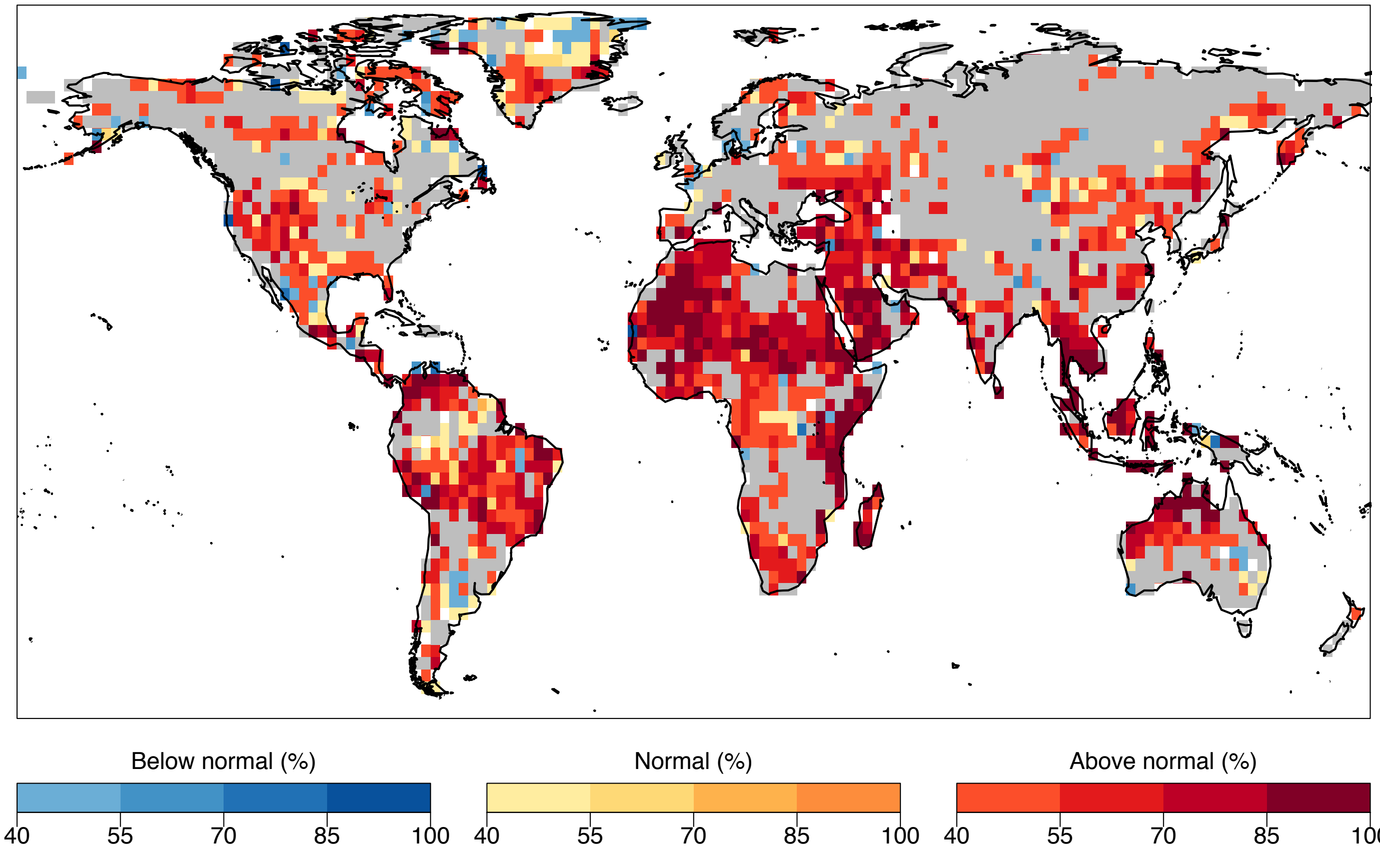
# Probabilistic forecasts: TXx




ECMWF S4 TXx forecast for MJJA 2016 (init. April).

# Probabilistic forecasts: TXx






ECMWF S4 TXx forecast for MJJA 2016 (init. April).

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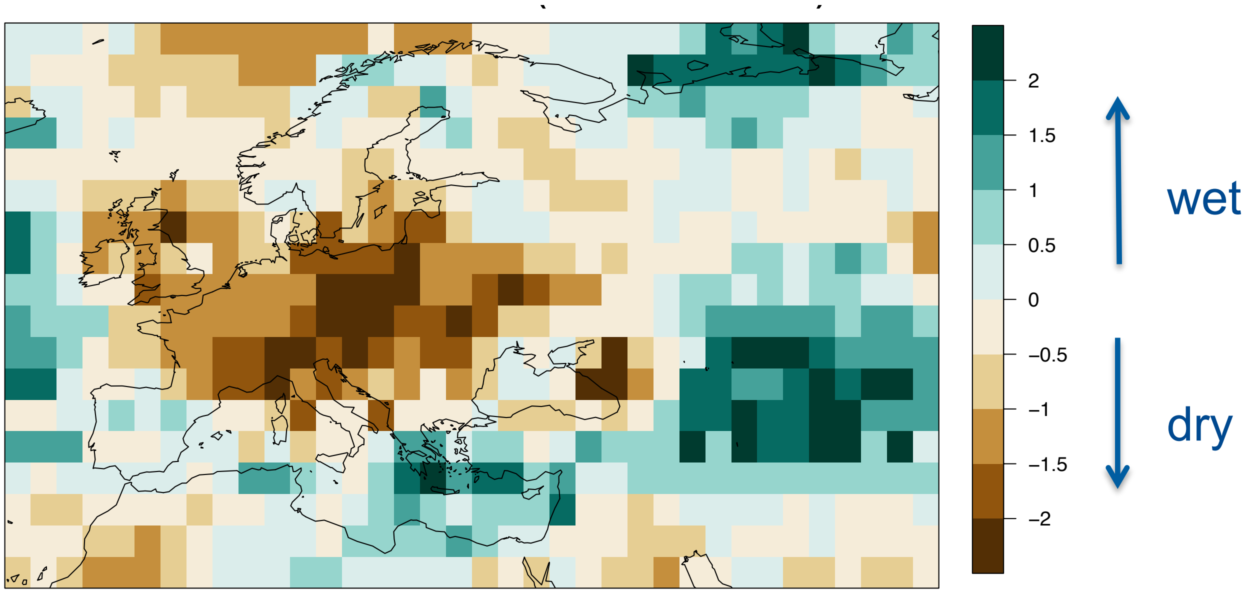
# Preliminary results: drought prediction



SPEI6 for June 2003




The Standardised Precipitation-Evapotranspiration Index (SPEI) is a multiscalar drought index based on the simultaneous use of precipitation and temperature fields: SPEI=f(P-PET)

While both SPI and SPEI have the advantage of providing a temporal multi-scalar character (being computed from 1 month up to 24 months), the SPEI holds the additional advantage of including the effects of temperature variability on drought assessment.

# Preliminary results: drought prediction



## Procedure to calculate the observed SPEI6 for June

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| O1 | … | … | 11 | 12 | O1 | O2 | O3 | O4 | O5 | O6 |

2003

$O_i = P_i - PET_i$

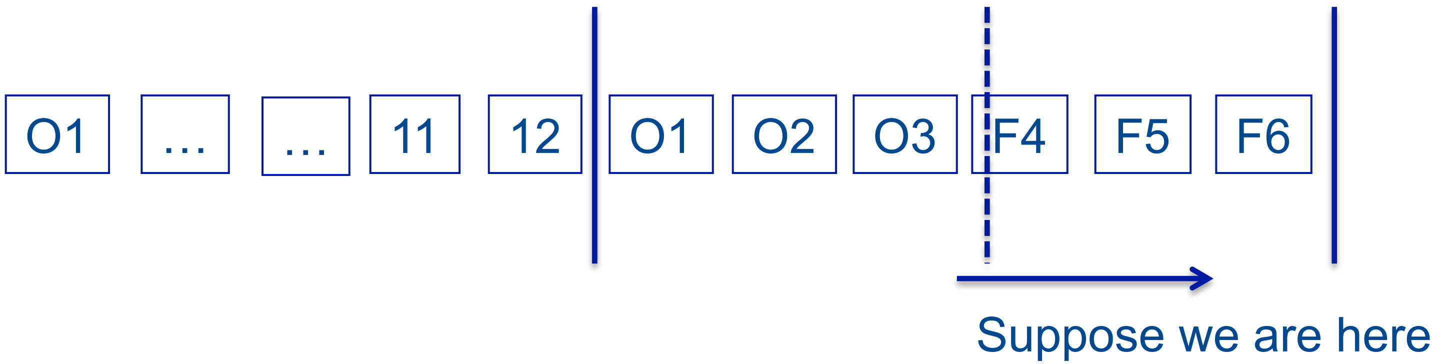
$A6_{2003} = O1+O2+O3+O4+O5+O6$

$SPEI6_{2003} = \text{Standardization}(A6_{2003}+A6_{2002}+\ldots+A6_{1981})$

More details of the SPEI index at http://sac.csic.es/spei/

# Preliminary results: drought prediction

## Procedure to calculate the **forecasted** SPEI6 for June




$F_i$= bias corrected Prec and Tmean

$A6_{2003}^{*}$= O1+O2+O3+F4+F5+F6

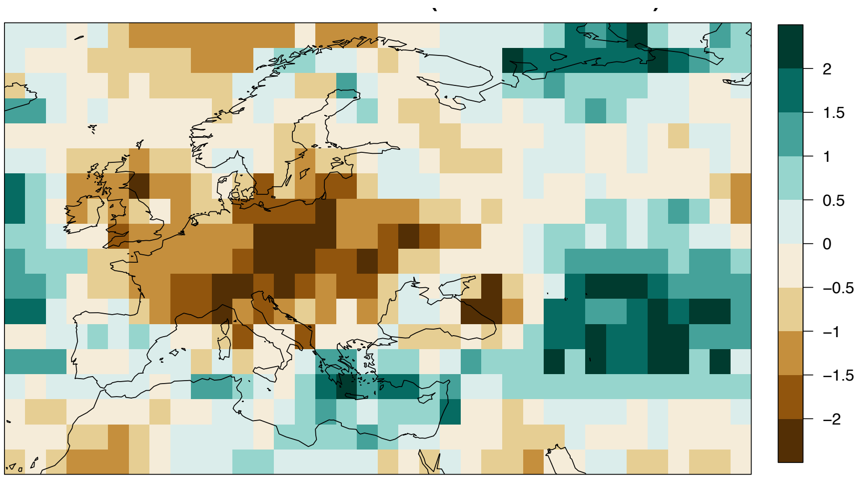
$SPEI6_{2003}^{*}$=Standardization($A6_{2003}^{*}$,$A6_{2002}$,…,$A6_{1981}$)

# Preliminary results: drought prediction

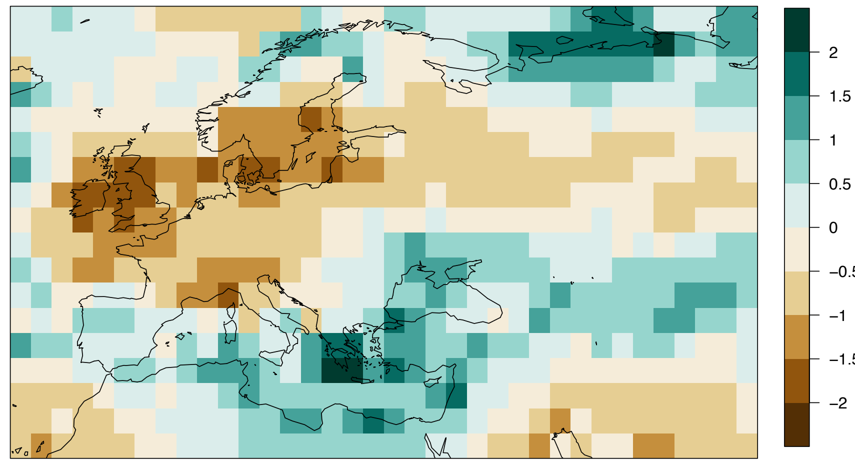


## SPEI6 for June 2003

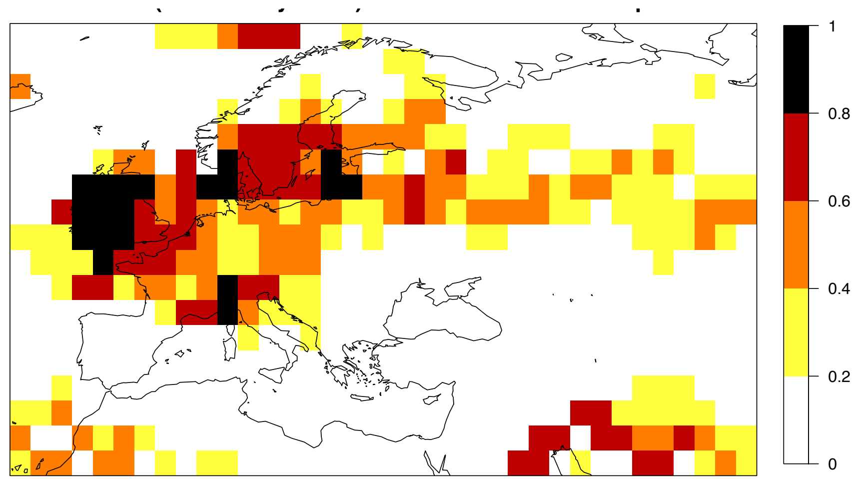
### Observed




### Forecasted - Ensemble mean



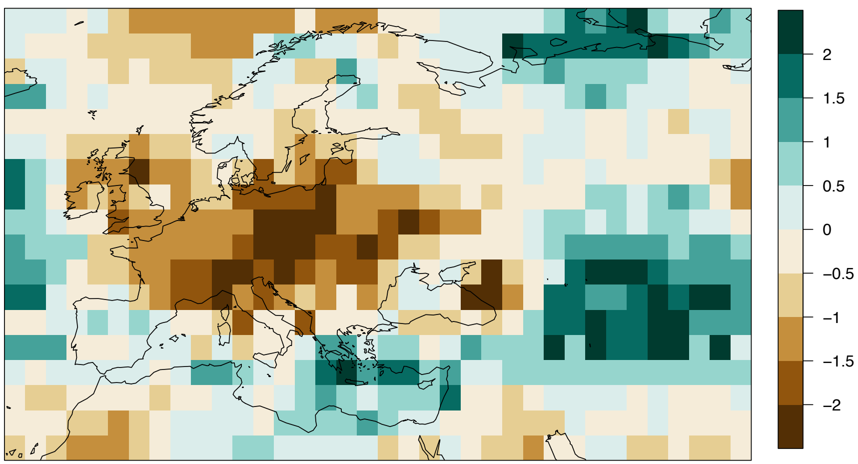

### Forecasted - Probability SPEI6 < -0.8



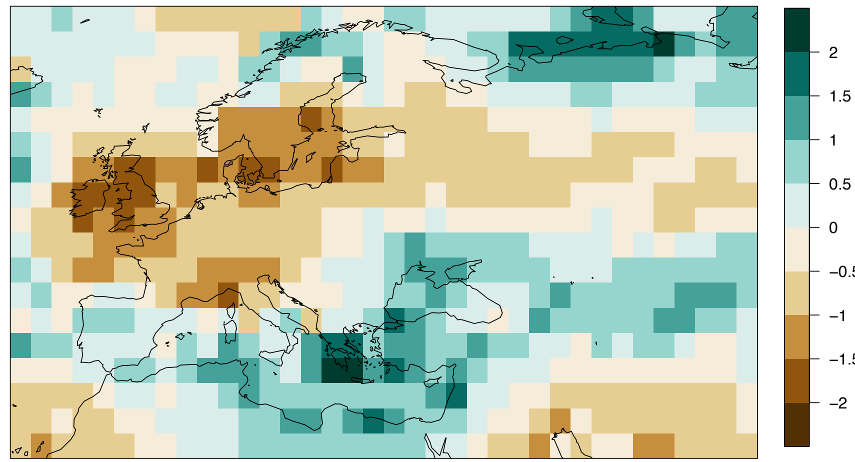
# Preliminary results: drought prediction

## SPEI6 for June 2003

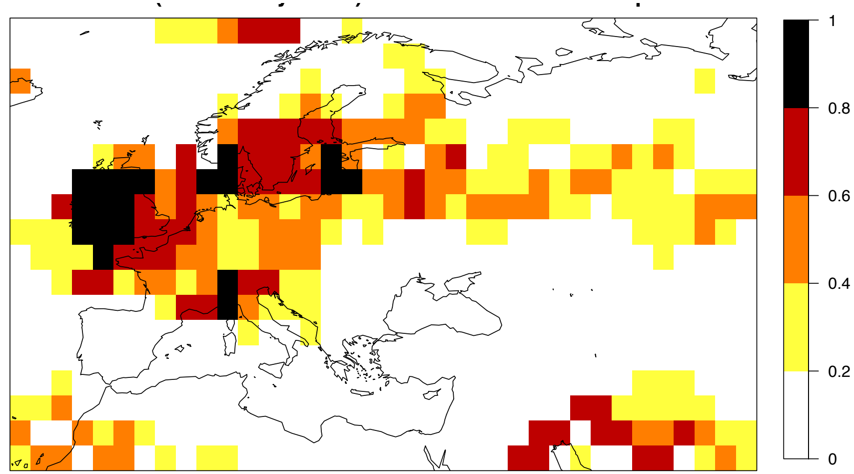
### Observed




### Forecasted - Ensemble mean




### Forecasted - Probability SPEI6 < -0.8



# Preliminary results: drought prediction

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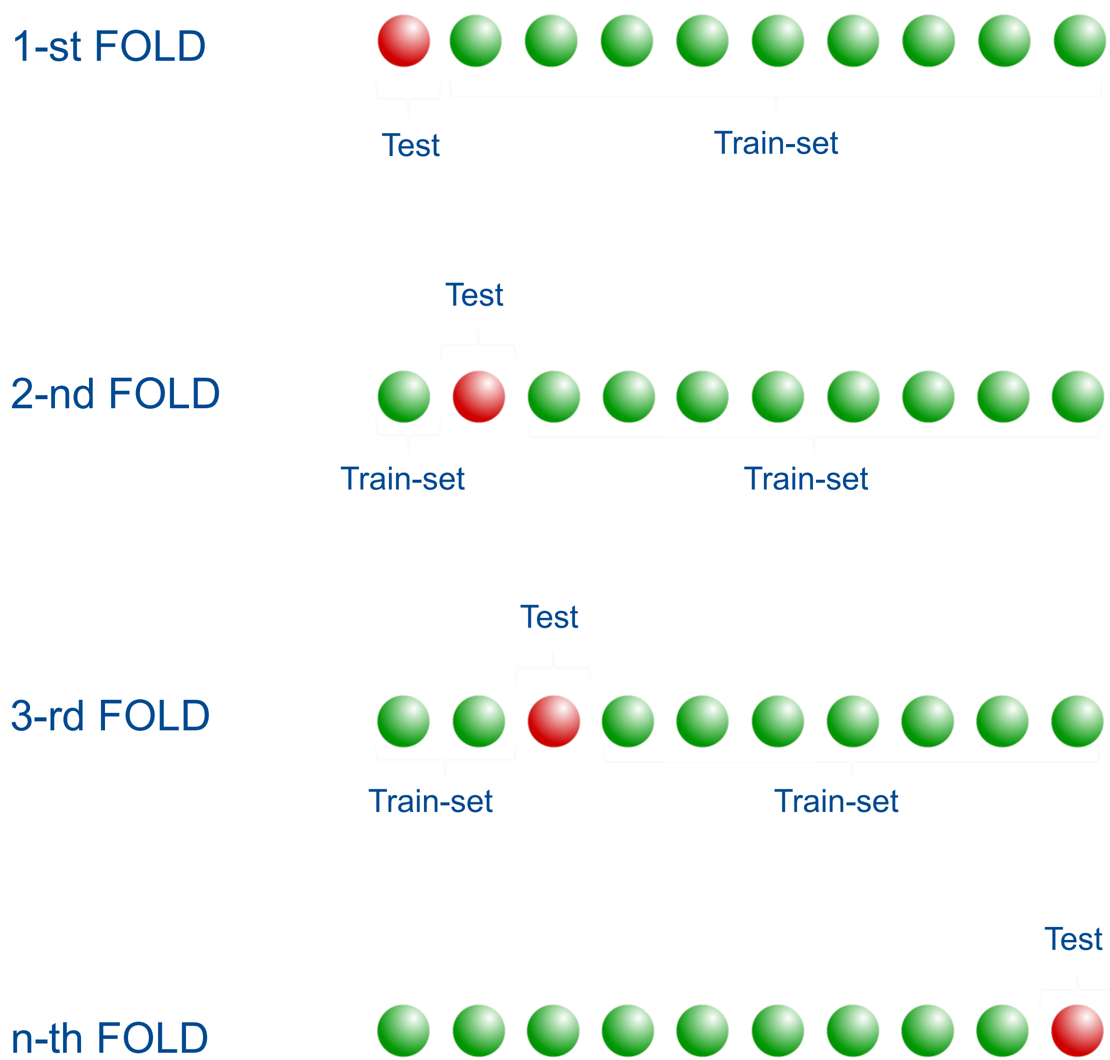
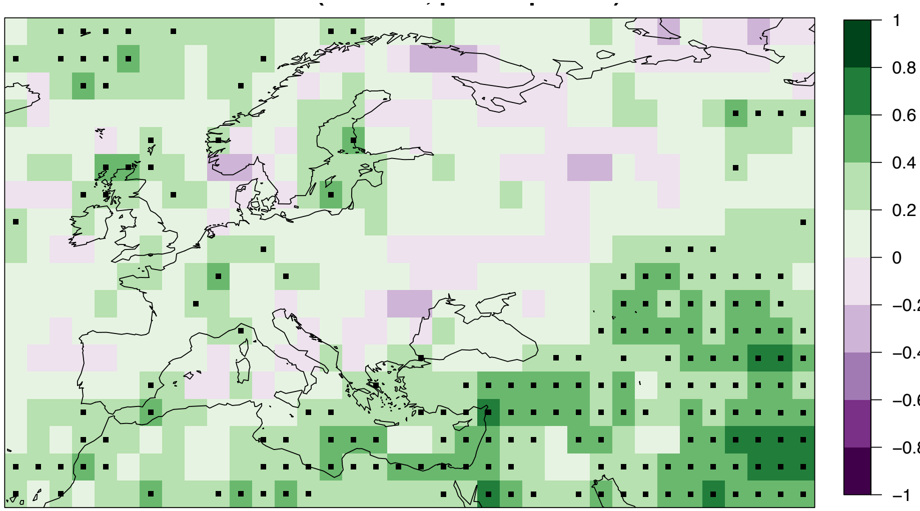
## Leave one out cross validation



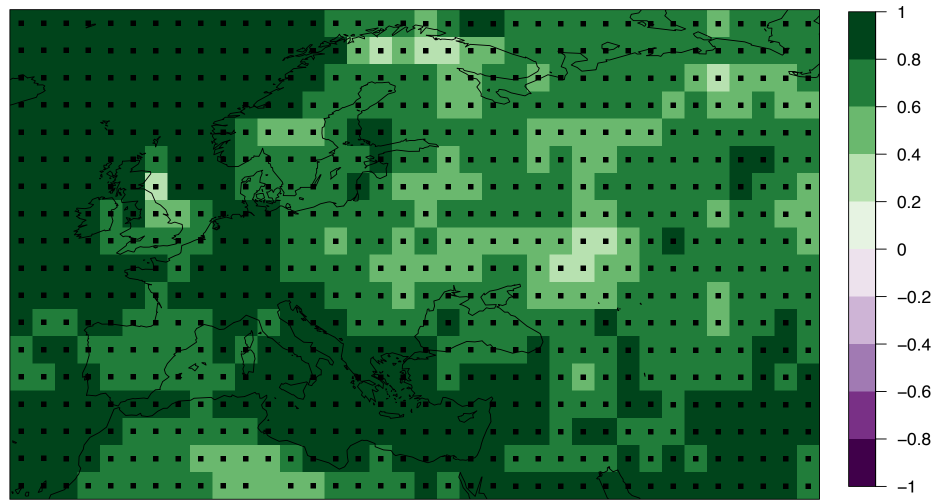
# Preliminary results: drought prediction

## Correlation of drought S4 forecasts wrt observed droughts over 1981-2014

### SPEI3 for June

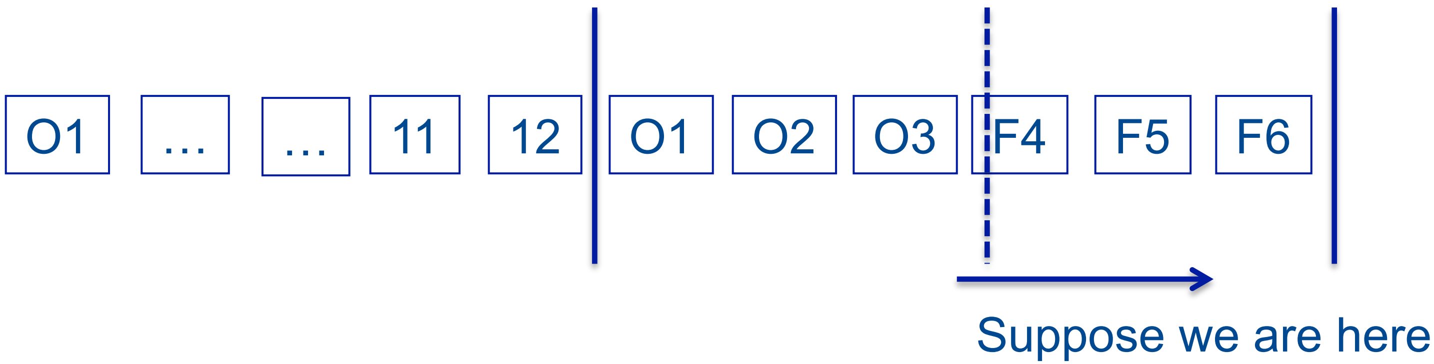



### SPEI6 for June



# Preliminary results: drought prediction

## Procedure to calculate the forecasted SPEI6 for June: Ensemble streamflow prediction (ESP), a benchmark




$F_i$= resampling of past observations

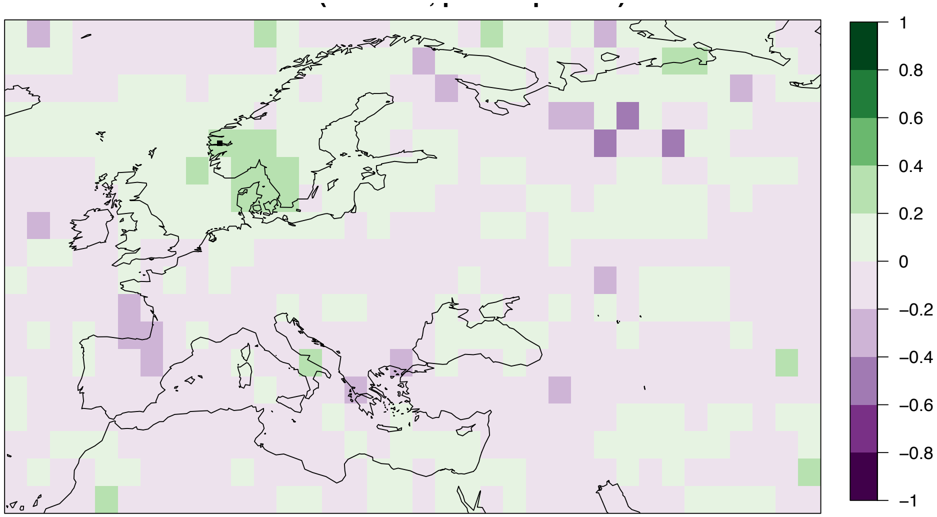
$A6_{2003}{}^{*}$= O1+O2+O3+F4+F5+F6

$SPEI6_{2003}{}^{*}$=Standardization($A6_{2003}{}^{*}$,$A6_{2002}$,…,$A6_{1981}$)

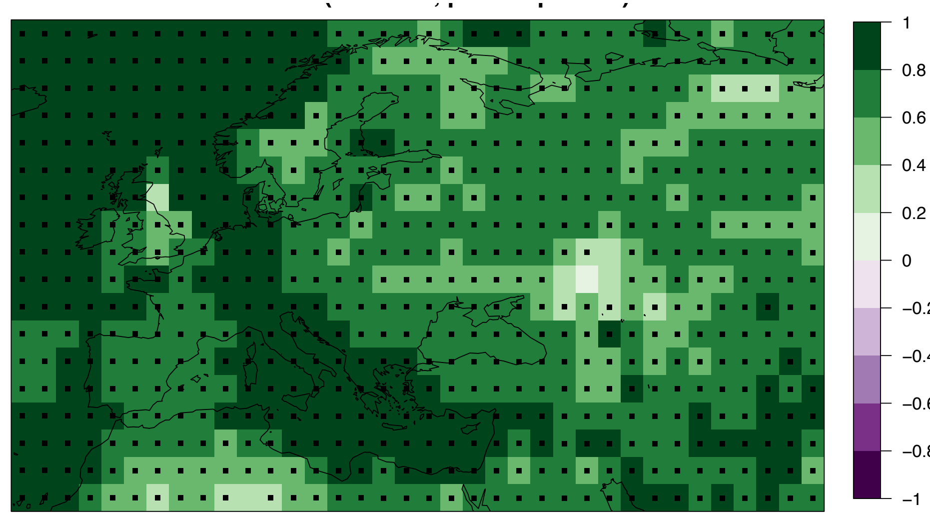
# Preliminary results: drought prediction

## Correlation of drought ESP forecasts wrt drought observation over 1981-2014

SPEI3 for June

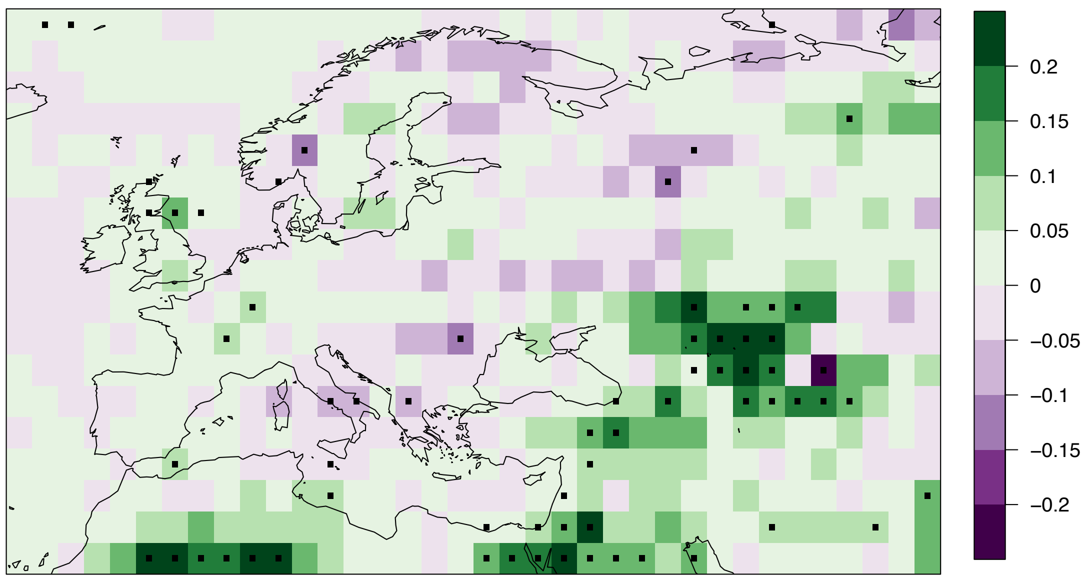



SPEI6 for June



# Preliminary results: drought prediction

## Difference of correlation of the ensemble mean between the S4 and ESP forecast for SPEI6 in June



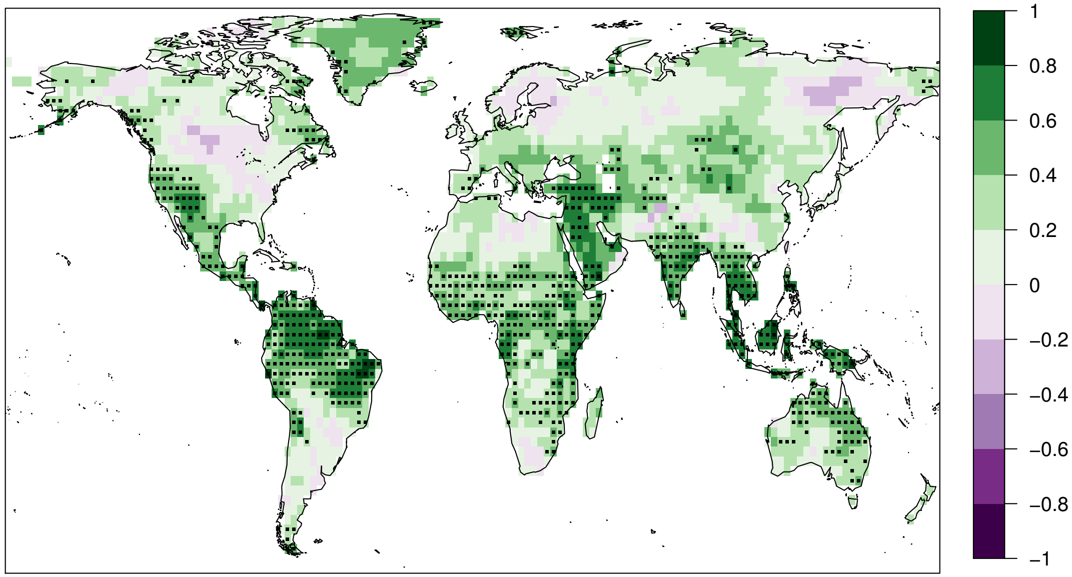

The *dots* mark the areas where the difference of correlation is significant at the 95 % confidence level

# Summary

- **Seasonal forecasts have some skill**. Probabilistic seasonal predictions can be used as a tool to inform agriculture users

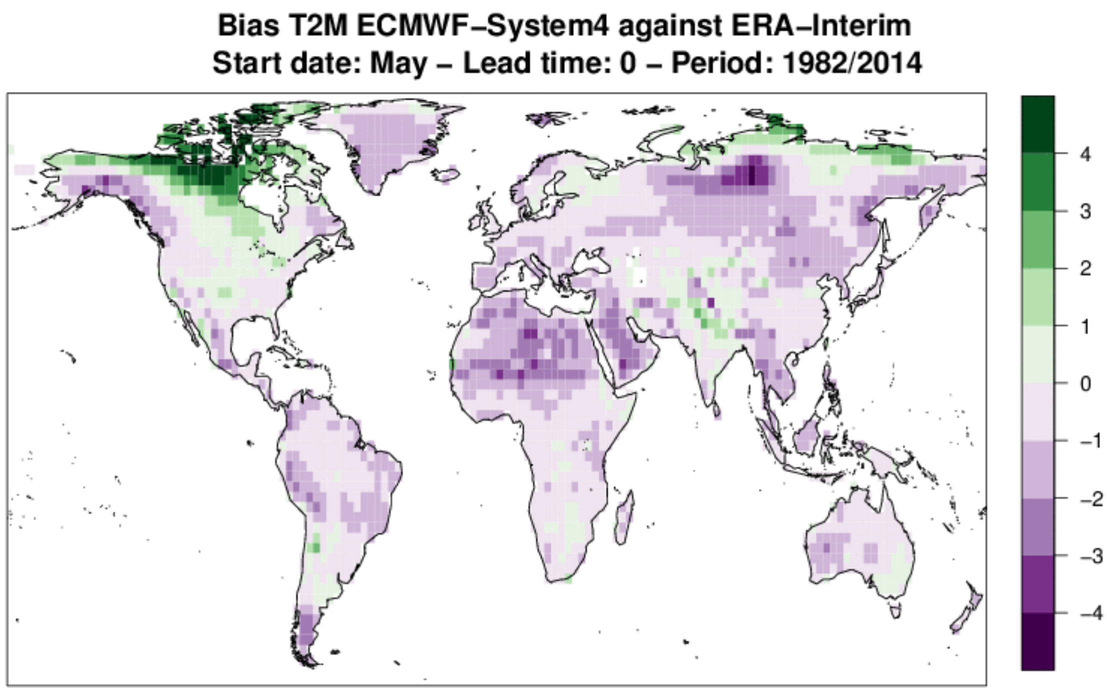
Correlation for t2m forecasts against ERA-Interim

June (May init.)



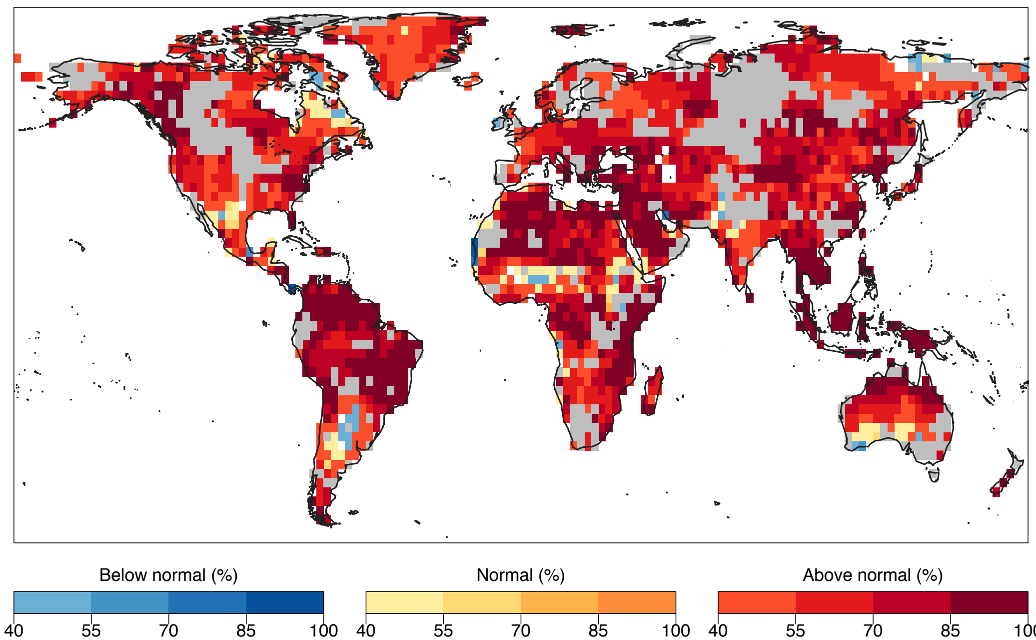
# Summary

- **Systematic errors**. Model drift is typically comparable to signal: mean biases are often comparable in magnitude to the anomalies which we seek to predict



# Summary

- Forecast quality assessment. There is the need to **extract climate information from climate data** and to define scores closer to the user through a process-based verification



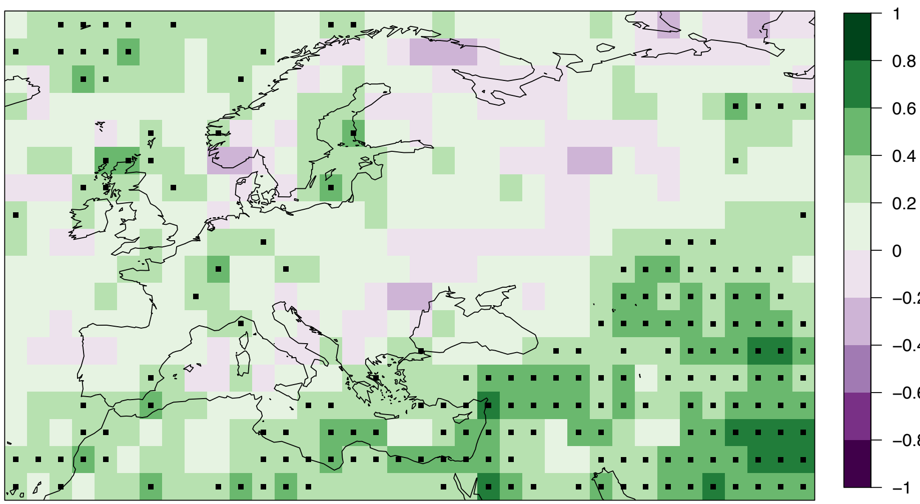

ECMWF S4 temperature forecast for MJJA 2016 (init. April).
Grey areas show where the climate prediction model doesn't improve the climatology.

# Summary

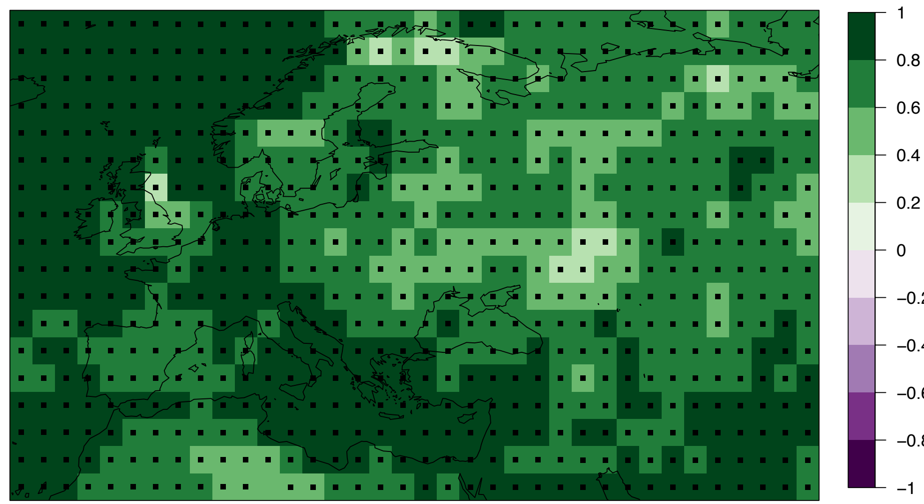
- Windows of opportunity for hybrid **dynamical–statistical prediction models** related to a better use of current benchmarks

Correlation of drought S4 forecasts
wrt observed droughts over 1981-2014

SPEI3 for June




SPEI6 for June



# Climate prediction and service activities



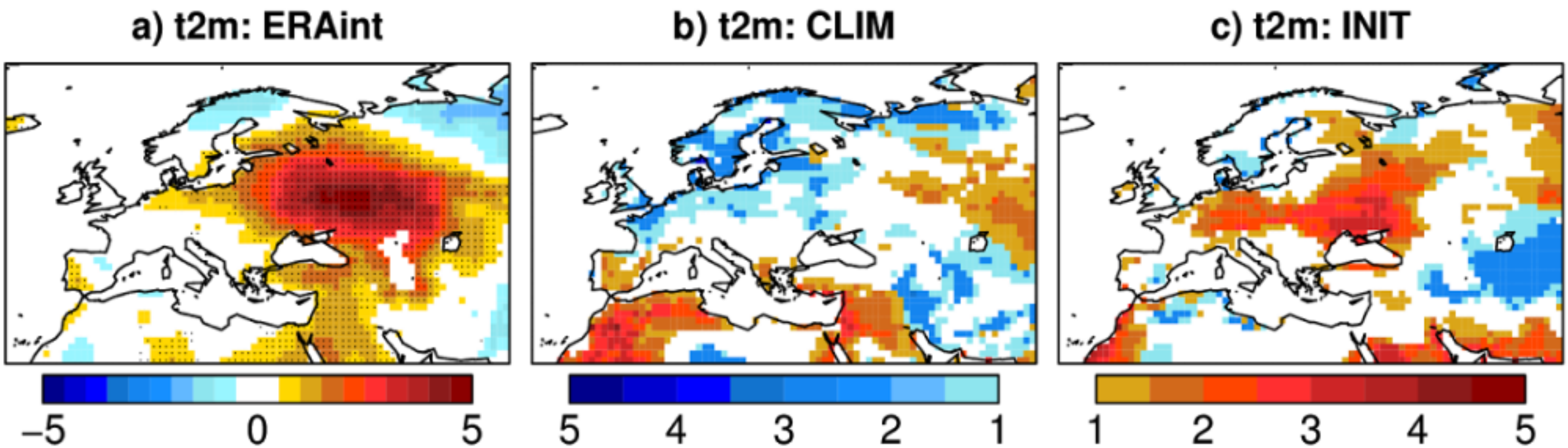
- Analyses of mechanisms leading to model bias and development of **bias correction techniques** accounting for sensitivity of bias to prediction start date

- **Improvement of forecast systems** through better process representation : inclusion of new parameterizations, new model components, high resolution, parameter calibration

- Identifying **sources of skill** such as **soil moisture**, sea ice thickness, aerosols, biogeochemistry through multi-faceted forecast quality assessment and sensitivity experiments

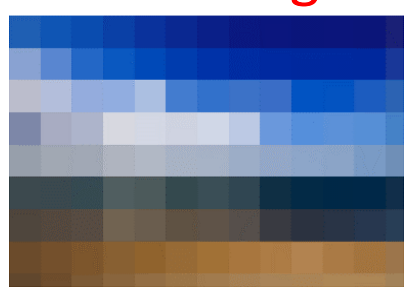
# Impact of land surface initialization

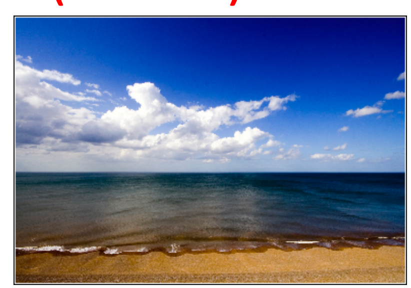
JJA near-surface temperature anomalies in 2010 from ERAInt (left) and odds ratio from experiments with a climatological (centre) and a realistic (right) land-surface initialisation. Results for EC-Earth2.3 started in May with initial conditions from ERAInt, ORAS4 and a sea-ice reconstruction over 1979-2010.




Similar results found for EC-Earth3 and high resolution (25 km).

Prodhomme et al. (2015, Clim. Dyn.)





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# Thank you!

For further information please contact:

**info-services-es@bsc.es**
**marco.turco@bsc.es**

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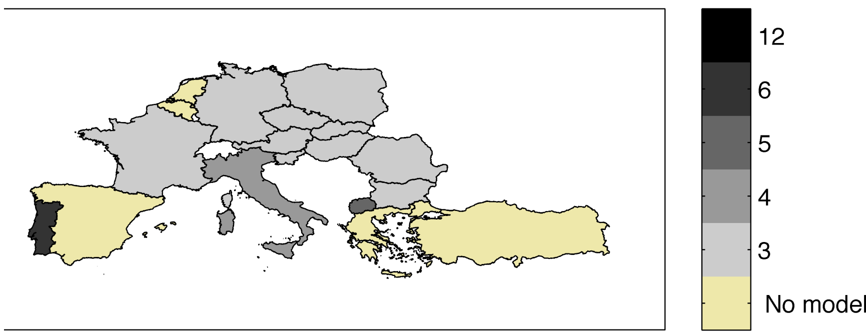
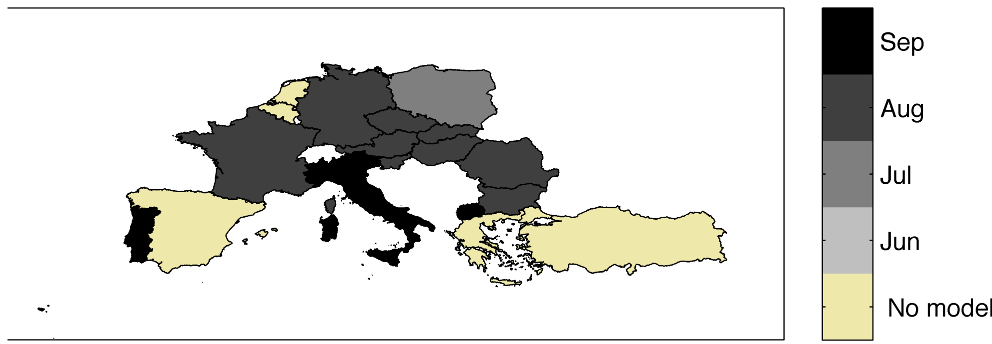
# EXTRA SLIDES

# Preliminary results: drought prediction

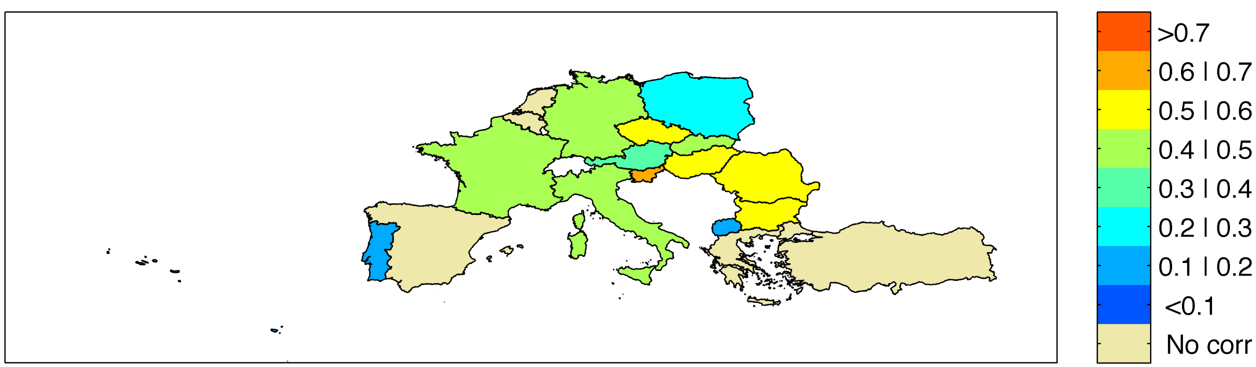


## Grain maize anomalies = f[SPEI$_x$(y)]




Variance explained by the Crop-SPEI model

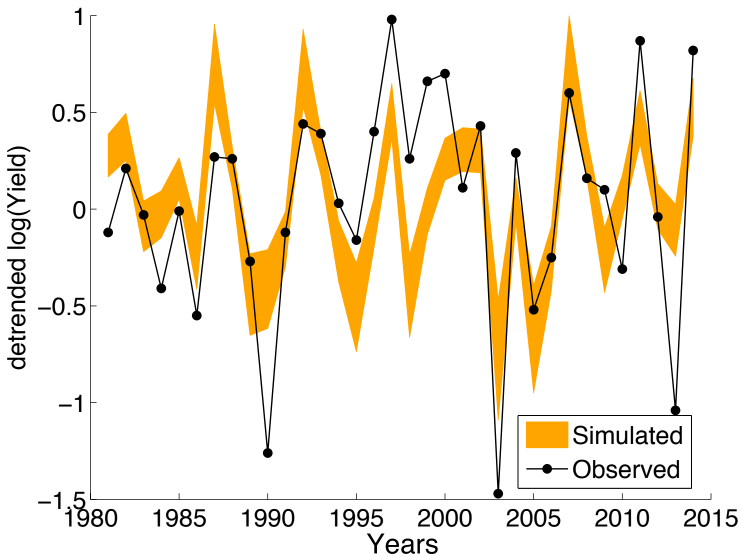


# Preliminary results: drought prediction

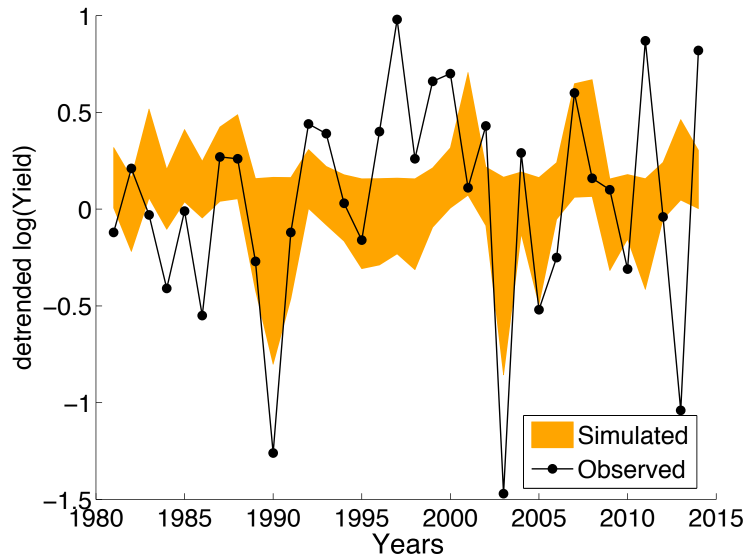
## Grain maize anomalies=f(drought)

France

SPEI3(8), $R^2$=0.49




SPEI6(8), $R^2$=0.14



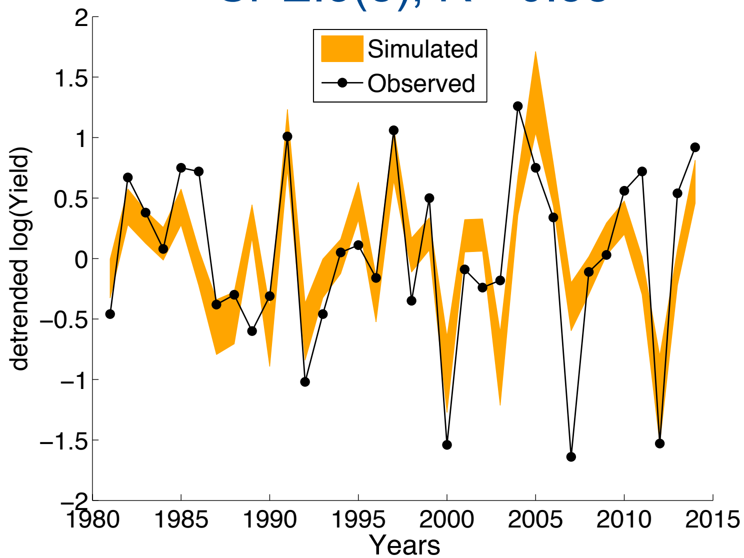

The orange shaded band includes 90 % of the members of 1000 different bootstrap replicates

# Preliminary results: drought prediction

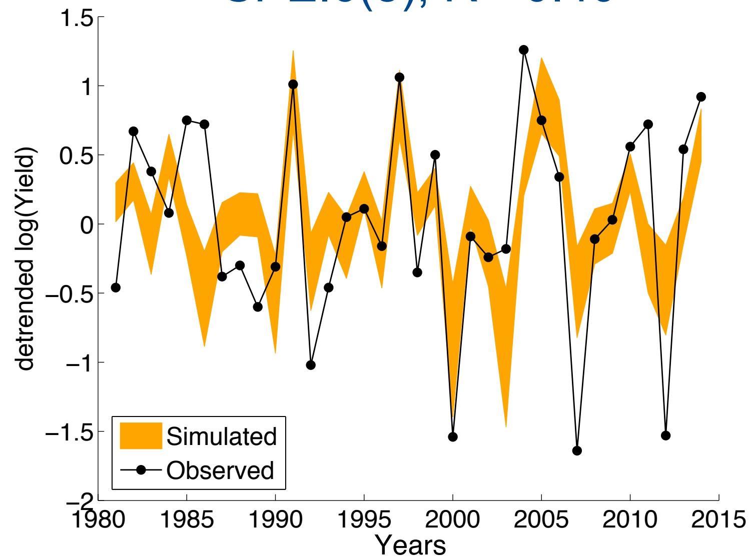
## Grain maize anomalies=f(drought)

Romania

SPEI3(8), $R^2$=0.58




SPEI6(8), $R^2$=0.40

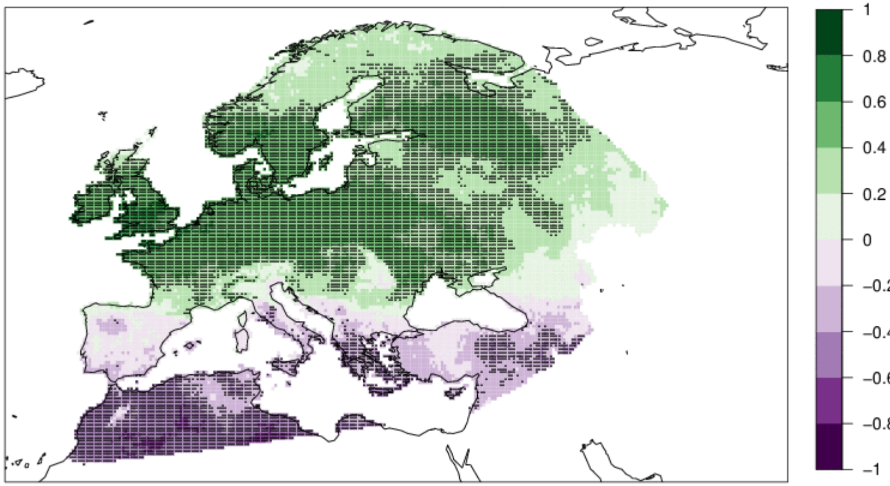



The orange shaded band includes 90 % of the members of 1000 different bootstrap replicates

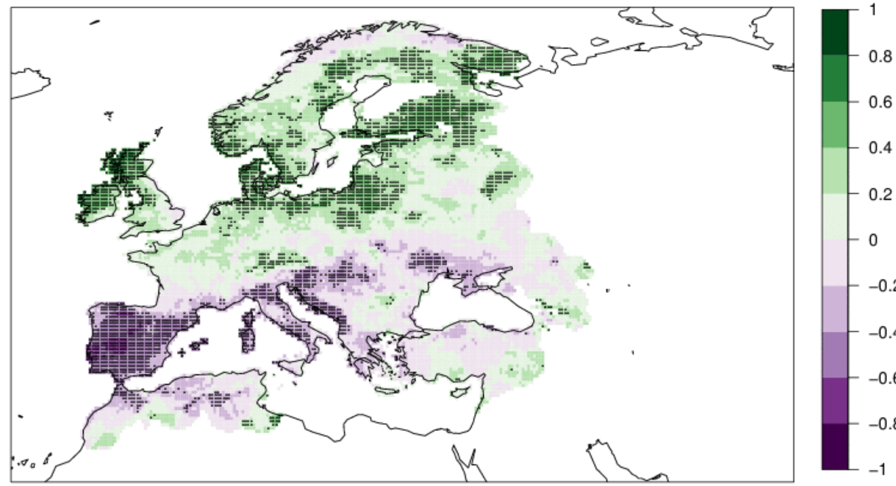
# Preliminary results: NAO->local climate→ crop yields



Spearman correlation
TMEAN(MARS) and NAO in January from 1986 to 2014
(detrended data; points: p<0.05)

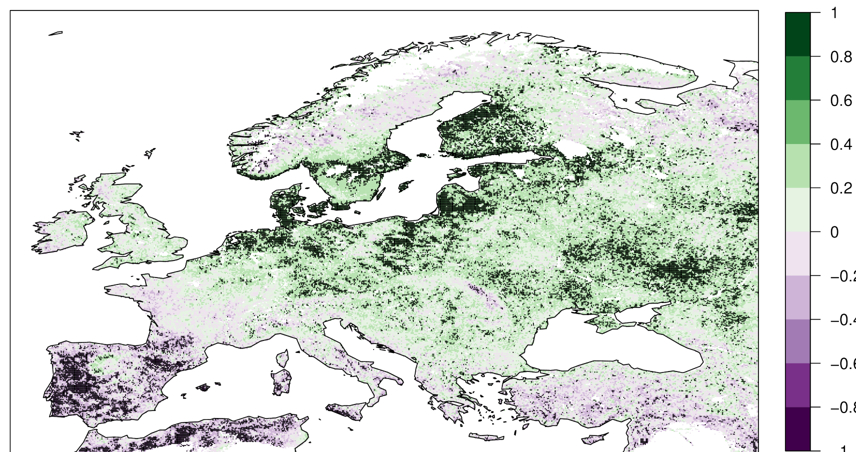



Spearman correlation
PRE(MARS) and NAO in January from 1986 to 2014
(detrended data; points: p<0.05)




Correlation of NAO and Tmean and Prec month by month

Spearman correlation
GIMMS NDVI in MAM and NAO in DJF from 1982 to 2011
(detrended data; points: p<0.05)




Correlation of NAO in winter and NDVI in spring

# Preliminary results:
# NAO->local climate→ crop yields

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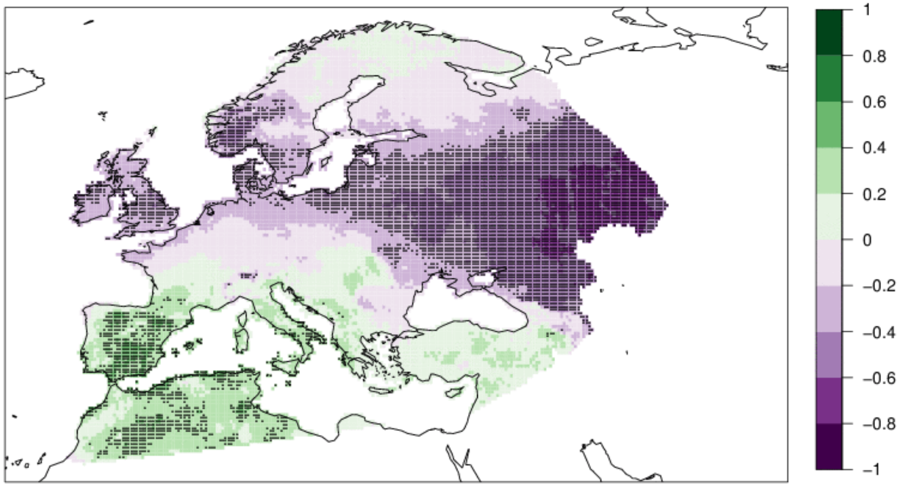
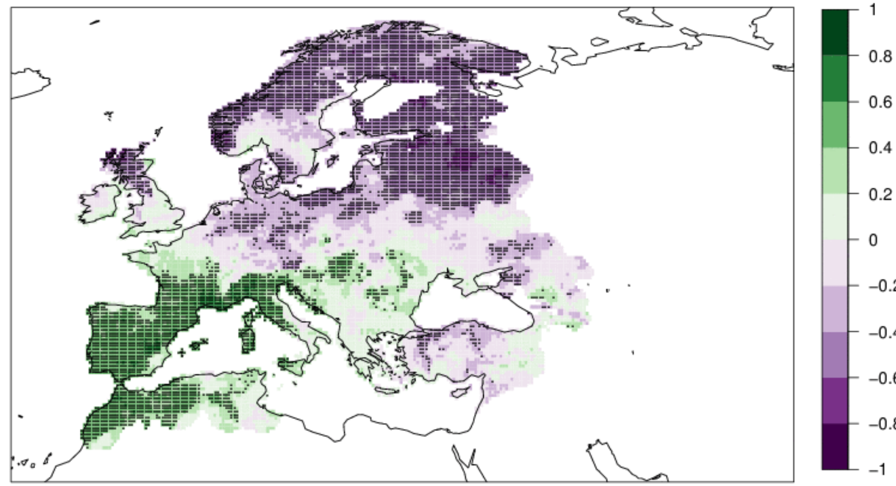
**Spearman correlation**
**TMEAN(MARS) and SCA in January from 1986 to 2014**
**(detrended data; points: p<0.05)**

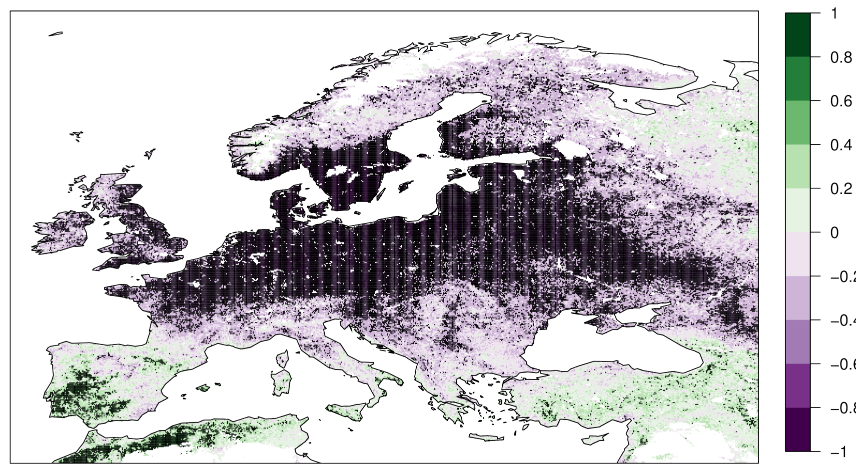



**Spearman correlation**
**PRE(MARS) and SCA in January from 1986 to 2014**
**(detrended data; points: p<0.05)**




Correlation of NAO and Tmean and Prec month by month

**Spearman correlation**
**GIMMS NDVI in MAM and SCA in DJF from 1982 to 2011**
**(detrended data; points: p<0.05)**




Correlation of NAO in winter and NDVI in spring

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## The Ranked Probability Skill Score (RPSS; Epstein 1969)

RPSS measures cumulative squared error between categorical forecast probabilities and the observed categorical probabilities relative to a reference forecast (e.g. climatology)

$$RPS = \frac{1}{M-1}\sum_{m=1}^{M}\left[\left(\sum_{k=1}^{m} p_k\right) - \left(\sum_{k=1}^{m} o_k\right)\right]^2$$

$$RPSS = \frac{\overline{RPS} - \overline{RPS}_{reference}}{0 - \overline{RPS}_{reference}} = 1 - \frac{\overline{RPS}}{\overline{RPS}_{reference}}$$

Where:
M is the number of forecast categories (3 for tercile forecasts)
pk is the predicted probability in forecast category k
ok is an indicator (0=no, 1=yes) for the observation in category

Range: minus infinity to 1; 0 indicates no skill when compared to the reference forecast. Perfect score: 1

# Preliminary results: drought prediction



## Leave one out cross validation

| 1981 | 1982 | … | … | 2013 | 2014 |
|---|---|---|---|---|---|

1. Select test year, the training period is the whole period without the test period
2. Calculate the observed and forecasted average over the training period: $<O>$, $<F>$
3. Bias correcting the forecasts: $P^*=P^*(<O>/<F>)$; $T^*=T-(<F>-<O>)$
4. Calculate $A6_{test}^{*}= O1+O2+O3+F4+F5+F6$
5. Calculate $SPEI6_{test}^{*}=\text{Standardization}(A6_{test}^{*},A_{training\_1}+\ldots+A_{training\_n-1})$; (n=number of years)